TRUST AND ANTI-AUTONOMY MODELLING OF AUTONOMOUS SYSTEMS

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

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ABSTRACT

Human trust in autonomous vehicles is built upon their safe and secure operability in the most ethical, law abiding manner possible. Despite the technological advancements that autonomous vehicles are equipped with, their perplexing operation on roads often give away telltale signs of underlying vulnerabilities to threats and attack strategies which can flag their anti-autonomous traits. Anti-autonomy refers to any conduct of autonomous vehicles that goes against the principles of autonomy and subsequently resulting in their immobilized operations during unexpected roadway situations. The concept of trust is fluid, which is made complicated by anti-autonomous behavior of autonomous vehicles and affects the dimensions of intentionality, human interaction, and adoption of autonomous vehicles. Trust is impacted by intentionality, safety and risks associated with autonomous vehicles and their overall perception by human drivers, pedestrians and bicyclist sharing the roads with them. The presence of collision data involving human drivers of other cars, pedestrian, bicyclists, resulting in injuries and damages poses a significant negative impact on trust in autonomous vehicle technology. This dissertation presents and evaluates a new and innovative anti-autonomy NoTrust Artificial Neural Network model by utilizing collision data reports involving autonomous vehicles provided by California DMV from October 2014 to March 2020, which is the latest reported data. This data was augmented, labelled, classified, pre-processed, and then applied towards creation of the NoTrust ANN model using linear sequential model libraries in Keras over Tensorflow. This model was used to predict trust in autonomous vehicles. The trained model was able to achieve 100% accuracy, which was evident in the results of model compilation and training, plots of validation and training accuracies and losses. Model evaluations and predictions were used to comprehend characteristics of trust, intentionality and anti-autonomy and helped establish a relationship between them and reflected

inter-dependencies among trust, intentionality, anti-autonomy, risk, and safety. Additional analyses of collision reports data was performed and the impact of several contributing factors of collisions such as vehicle driving mode, damages sustained by the vehicle, pedestrian and bicyclist involved in collisions, weather conditions, roadway surface, lighting conditions, movement of vehicle preceding collision and type of collisions was illustrated.

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I would like to express my immense gratitude towards Dr. Kendall Nygard for extending the opportunity to pursue my research work under him. I would also like to thank Dr. Pratap Kotala, Dr. Zubair Malik and Dr. Limin Zhang for their valuable presence as my committee members. Special thanks to Dr. Zubair Malik for agreeing to be on my committee on such a short notice.

I would also like to thank my family (my Mom, my Dad, and my Brother) for their blessings and providing me with constant support and motivation and having faith in me. Words falls short to describe their efforts in boosting my morale and providing me strength to march through and work hard.

DEDICATION

I would like to dedicate this to my Mom, for her unconditional love, support, and care. Thank you, Mom, for taking pride in me and being my pillar of support while guiding me through the challenges of life.

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LIST OF ABBREVIATIONS

ANN...Artificial Neural Network

DMV ....Division of Motor Vehicles

ISCA ....International Society for Computers and their Applications

SEDE..Software Engineering and Data Engineering

ICJA ....International Journal of Computers and their Applications

HCI...Human Computer Interaction

OCR ....Optical Character Recognition

CART...Classification and Regression Trees

AI ....Artificial Intelligence

SAS ....Semi-autonomous systems

HITL ....Human-in-the-Loop

RAS..Semiautonomous Robotic Systems

HOTL...Human-on-the-Loop

MCAS ....Maneuvering Characteristics Augmentation System

EEGs ....Electroencephalograms

SCR..Software Cost Reduction

IDS ....Intrusion Detection Systems

CATS ....Cooperating Autonomous Detection Systems

IEDs ....Improvised Explosive Vevices

UAVs ....Unmanned Aerial Vehicles

GPS ....Global Positioning System

C-UAS..Countering Unmanned Aerial Systems

BGP..Border Gateway Protocol

PGBGP..Pretty good BGP

IP...Internet Protocol

DNS..Domain Name System

ABS..Anti-lock Braking Systems

MOD...Moving Object Detection

QSCSIMS...Quality Safety Cyber Security Integrated Management System

VANETs...Vehicular Ad-hoc Networks

V2V...Vehicle to Vehicle

RSUs...Road Side Units

LiDAR...Light Detection and Ranging

BMW...Bayerische Motoren Werk

OBD..On-Board Diagnostics

DSRC..Dedicated Short Range Communications

USB...Universal Serial Bus

SMS...Short Message Service

CAN..Controller Area Network

DoS...Denial of Service

ICMetric-IDS...Integrated Circuit Metric – Intrusion Detection System

SGSD..Social Graph-based Sybil detection

BCSD..Behavior Classification-based Sybil detection

OTA..Over-the-Air

CVC..Connection Vehicle Cloud

DDoS..Distributed Denial of Service (DDoS)

ADAS..Advanced Driver Assistance System

SAE	Society of Automotive Engineers
NHTSA	National Highway Traffic Safety Administration
DOT	Department of Transportation
V2I	Vehicle to Infrastructure
FMVSS	Federal Motor Vehicle Safety Standards
USDOT	US Department of Transportation
DOE	US Department of Energy
NSF	National Science Foundation
NASA	National Aeronautics and Space Administration
SMART	Systems and Modeling for Accelerated Research in Transportation
EEMS	Energy Efficient Mobility Systems
NEXTCAR	Next-Generation Energy Technologies for Connected and Automated On-Road Vehicles
FTC	Federal Trade Commission
GAO	U.S. Government Accountability Office
SELF DRIVE	Safely Ensuring Lives Future Deployment and Research In Vehicle Evolution
ADS	Automated Driving Systems
HAVs	Highly Automated Vehicles
AV START	American Vision for Safer Transportation Through Advancement of Revolutionary Technologies
PDF	Portable Document Format
CSV	Comma-Separated Values
APIs	Application Programming Interfaces
CPU	Central Processing Unit
GPU	Graphics Processing Unit

IDE..Integrated Development Environment

relu ....Rectified Linear Unit

adam..a stochastic optimization method

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CHAPTER 1. INTRODUCTION

Autonomous vehicles were launched with a promise to proudly establish a safe and low effort driving experience that would significantly aid humans in travel to assist with many daily chores. However, many benefits of automation have a plethora of cybersecurity issues, threat vulnerabilities, ethical and legal issues. The behaviors of human drivers, pedestrians, and bicyclists with which autonomous vehicles share the roads, are capable of paralyzing the internal mechanics of autonomous vehicles, leading to chaos, confusion, collisions, and related traffic issues on the roads. Situations like these highlight the anti-autonomous, non-intuitive, unethical and collision prone attribute of autonomous vehicles. In order to expand the knowledge and understanding of the concept of anti-autonomy, learn about its impact on human trust in autonomy along with gaining insights on the potential threats that autonomous vehicles are prone to, extensive research work was performed and published as journal and conference proceeding articles. The contributions made in these published articles progressed into leading towards the quest to search for collision data caused by autonomous vehicles. Once the data was procured, an extensive in-depth analysis of data was performed, and the data was appropriately conditioned to be utilized towards generation of anti-autonomy model. The purpose of the research work in this dissertation is to develop and demonstrate an anti-autonomy model to help

- disseminate well researched information about the factors responsible behind autonomous vehicle collisions and accidents and help manufacturers to improve upon the implementation criteria of sensors, vehicle internal dynamics and mechanics and so on

- people gather information about autonomous vehicles through the model predictions and evaluations and make informed decisions before adopting and owning autonomous vehicles

This chapter describes the purpose of this research study and the motivation behind it. It then describes the problem statement and then lays out the overall organization of the entire dissertation.

1.1. Purpose

Autonomous vehicles are designed to operate safely and securely without any human intervention while also strictly abiding the traffic laws. Manufacturers of these vehicles work vehemently towards the safety and security aspects by actively employing white-hat hackers to effectively minimize threats, vulnerabilities and hacking attacks, but is it enough for common human drivers to give them a peace of mind and place their trust into adopting these vehicles? Even with the most advanced automation technology with state of the art ethics incorporated into it, these vehicles may still not be fail-safe when their ethical behavior and intuitiveness is challenged while sharing the roads with human drivers, pedestrians, and bicyclists. Despite the most advanced technological features, a single accident and/or collision report can surface the negative and anti-autonomous aspect of autonomous vehicles. Hence, it becomes paramount to carefully study, investigate, and explore the factors and attributes of autonomous vehicles that are capable of highlighting the anti-autonomous aspect of autonomous vehicles and negatively impact their associated intentionality, safety and security and lead to diminishing trust in their potential adoption.

1.2. Motivation

Autonomous vehicles are a present day reality with thousands of millions of miles of recorded driving logs with or without the presence of a human driver in the car on standby to disengage and take control in the event of unprecedented situation on the road. Abundance of literature in detailed analysis of the automated driving data and surveys on the adoption of autonomous vehicles have tried to bring forth the best of technological advancements in automation, however, seldom research has been done to bring forth the anti-autonomous side of these autonomous vehicles. The motivation behind this research study is to bring forward the anti-autonomous side of the autonomous vehicles and establish a quantifiable relationship of anti-autonomy with multidimensional concepts of trust, intentionality, risk, and safety as they relate to automation technology. The anti-autonomy trust modelling demonstrated in this dissertation aims to disseminate the awareness about the anti-autonomous traits of automation technology with the hope to help people make informed decisions while approaching towards trusting and adopting autonomous vehicles.

1.3. Goals and Objectives

Collisions and accidents caused by human drivers can be judged, explained, and rationalized on the basis of consciousness, state of mind of the human driver, whether or not the human driver was under influence. However, the collisions and accidents caused by autonomous vehicles cannot be explained and rationalized using the same attributes since these vehicles are supposed to eliminate these causes of collisions and provide a safer less congested travel experience on the roads. This brings up a question as to how a situation of collision involving autonomous system would be explained. Collisions involving autonomous vehicles instigates its irrational driving aspect and surfaces the anti-autonomous traits of autonomous vehicles. This encouraged the need to create this anti-autonomy model to effectively help study, analyze and understand the reason behind the anti-autonomous trait of autonomous vehicles.

The research work in this dissertation was commenced with the objective of creating an anti-autonomy model to understand and explain the anti-autonomy traits that autonomous vehicles exhibit during their erratic driving traits on the roads. While other research in the area of autonomous vehicle lean towards the promotion of extra-ordinary features and positive aspects of autonomous vehicles, this anti-autonomy model aims to bring forth the significance of exploring and understanding the root cause behind the anti-autonomous activities of these vehicles and effectively working towards mitigating them.

The goal of the research work demonstrated in this dissertation is to advance the state of the art in anti-autonomy via the development and validation of the anti-autonomy model. This was achieved by the fulfilling the several tasks in order. The configuration of the overall model was done by acquisition of data from collision reports. Upon acquiring, processing, cleaning, and managing data, the model was populated which was capable of ingesting this data and produce desired results. These results were then used to make predictions and evaluations which was then utilized to establish a relationship between trust, intentionality, anti-autonomy, risk, and safety. The evaluations also helped with throwing insights to the overall security aspects associated with autonomous vehicles.

1.4. Problem Statement

In the context of Autonomous vehicles, despite the extensive prior research on pros and adaptability of these vehicles, there is a dire need to understand the underlying security issues, explore the avenues of their anti-autonomous capabilities, enlist a myriad of related legal and ethical issues and policies and, identify and analyze security threats. Additionally, establish a relationship of anti-autonomous traits of autonomous vehicles with the multi-dimensional aspects of trust, intentionality, risk, and safety and quantifying these measures. Pertaining to these needs this research study developed and demonstrated a data-centric anti-autonomy/trust ANN model with the application of machine learning concepts utilizing TensorFlow with Keras.

1.5. Peer-Reviewed Publications

In context of this dissertation, three papers were published out of which two papers were published as conference articles and one paper was invited to be published as journal article. Aakanksha Rastogi is the primary author of all these published papers and is responsible for research work illustrated in them with author's academic advisor as the co-author. In Dr. Nygard's role as academic advisor, he provided the significance of research problem and research area and advised on exposition and helped with editing the document. The actual research contributions and the research pertaining to the papers is the full responsibility of Aakanksha Rastogi. The Paper titled 'Trust Issues in Cybersecurity and Autonomy' in 'ISCA 27th International Conference on Software Engineering and Data Engineering' [1] was invited for expansion and submission to SEDE special edition ICJA journal. Journal article titled 'Trust and Security in Intelligent Autonomous Systems' was published in ICJA which is used as Chapter Three in this dissertation [2]. Conference Proceeding article titled 'Threat and Alert Analytics in Autonomous Systems' was published in 'Proceedings of the 35th International Conference on Computers and their Applications' is used as Chapter Four in this dissertation [3].

1.6. Dissertation Organization

This dissertation is organized as and composed of eight chapters. Chapter One discusses the purpose of developing and demonstrating a NoTrust ANN Model and why is it vital. This chapter also includes the problem statement which discusses the main focus of this research work.

Chapter Two provides the literature review and the background of this NoTrust ANN Model and existing work that has been done in this area.

Chapter Three is a published journal article titled 'Trust and Security in Intelligent Autonomous Systems' from SEDE special edition ICJA journal [2]. Aakanksha Rastogi is the sole primary author and claims the research work published in this article. The co-author of the article is author's academic advisor who advised on the background literature and helped with editing the document. This chapter (journal article) discusses the concepts of trust as they relate to humans and autonomous systems, provides an ontology to characterize that relationship and describes the trust issues pertaining to the areas of cybersecurity and autonomy. This chapter also establishes the concept of anti-autonomy and counter measures that apply to autonomous weapon systems.

Chapter Four is a published conference proceeding article titled 'Threat and Alert Analytics in Autonomous Systems' from Proceedings of the 35th International Conference on Computers and their Applications [3]. Aakanksha Rastogi is the sole primary author and claims the research work published in this article. The co-author of the article is author's academic advisor who helped with editing the document. This chapter (conference proceeding article) explores, identifies, and addresses popular threats, vulnerabilities, and hacking attacks to which autonomous vehicles are prone to and establishes a relationship between threats, trust, and reliability. It also presents an analysis of the alert systems in autonomous vehicles.

Chapter Five discusses the ethical relationship between humans and autonomous systems and identifies, studies, and characterizes the policies, ethical and moral values and, legal issues as they relate to autonomous vehicles.

Chapter Six presents a data-centric NoTrust ANN model to understand, characterize and analyze collision reports of traffic incidents involving autonomous vehicles with the help of deep learning and machine learning concepts and algorithms. The model evaluation and predictions are utilized to identify, derive, and quantify a relationship between trust, intentionality, anti-autonomy, risk, and safety.

Chapter Seven concludes the research work in this dissertation.

Chapter Eight discusses the limitations of this work and future work that can be done in this area.

An Appendix enlists the comprehensive information about the dataset generated from the PDF versions of the collision reports provided by California DMV which involved autonomous vehicles, screen capture of sample PDF reports and screen capture of CSV data file.

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CHAPTER 2. LITERATURE REVIEW

Vehicles with no automation and semi-autonomous vehicles, provide us with a thrill to drive them through traffic situations in cities of less traffic areas on freeways, allowing us to develop an interaction relationship with them. However, with the case of autonomous vehicles, them becoming an agent self-reliantly navigating themselves, changes the interaction relationship between human and machine. According to Daily et. al., "the design of intelligent driver-assistance systems, especially those that activate controls of the car to prevent accidents, requires an accurate understanding of human behavior as well as modeling of human–vehicle interactions, driver activities while behind the wheel, and predictable human intent" [4]. Brown and Laurier studied publicly available videos of Tesla auto-pilot and Google self-driving cars to infer the interaction of drivers of these cars with the drivers of other cars in terms of actions of these cars while sharing the road with other drivers [3]. Considering the challenges that drivers with autopilots experience, and while focusing on the social interaction on the road, communication among drivers and their interpretation of the movement of cars; they suggested increasing the transparency of the actions of autopilots for both the drivers of these cars as well as other cars that are sharing the road [3]. Their study aimed to insinuate avoidance of the dangers of badly designed autopilots while promoting the benefits of HCI in helping design better autopilots [3].

Wolf studied human interaction with autonomous vehicles by looking into the cognitive-psychological effects of the interaction of machine with humans [11]. He described the human factors in autonomous vehicles and stated that human knowledge and learning experiences in forms of mental models (a cognitive psychology concept) helps understand and design the interaction between technical systems and humans [11]. Mental models help describe human information processing and serve as a means to conceptualize functional assumptions and representations of knowledge in turn helping understand and predict how users behave while interacting with automated systems [11]. In a similar study by Surden and Williams, authors utilized concept of ‘theory of mind’ to describe human ability and possession of an internal mental model in reliably predicting and assessing the motivations, beliefs, mental states, actions, intentions, and future conduct of other people [9]. This ability to predict the behavior of others is one aspect of theory of mind which can significantly help reduce risk of collision and physical harm. Humans can observe the gestures, facial expressions, and movements, interpret them and react accordingly [9]. However, the complexity, abstractness and opacity of machine learning models employed in autonomous vehicles makes it hard for the programmers to predict and understand their next move, thus posing difficulties in human-autonomous vehicle understanding and cooperation.

Despite the complexity of autonomous vehicles, their involvement in collisions in recent years, has severely implications in their trust and adoption. Reports of traffic collisions involving autonomous vehicles has been generated, made publicly available, explored, studied, analyzed and worked on by some researchers in distinct ways. Yu and Grembek presented an end-to-end data processing and collision analysis system for autonomous vehicle crash reports from October 2014 to 2018 [12]. They first created a web crawler application and used data scraping techniques to download the crash reports from California DMV website and then used convolution and optical character recognition (OCR) techniques to extract the data. This OCR text file was then used to extract more information using natural language processing [12]. They then analyzed 41 crash reports from 2018 where vehicles were operating in autonomous mode and reported that 76% collisions happened at intersections, 20% of collisions were side-swipe and 66% were rear-end where autonomous vehicle was stopped [12]. Authors deduced this to be the impatience or misunderstanding of other human drivers due to conservativeness of autonomous vehicles or its abrupt behavior of slowing or braking [12].

Dixit et. al. studied the collision reports data to understand the trust in autonomous vehicles, disengagement and accident exposure and driver reaction times and deduced a correlation between collisions and autonomous miles travelled that was significant enough to be potentially used as a measure of exposure for disengagements [6]. They also found evidence which suggested that lack of trust caused an increased likeliness of taking manual control of the vehicle and reduction in reaction times [6]. In their study on examination of accident reports involving autonomous vehicles in collision, Favarò et. al. reported 62% of collisions in autonomous diving mode, 19% collisions in conventional driving mode, 15% collisions when manual disengagement was made before collision and 15% collisions when manual disengagement was made after collision [8]. In another study on disengagement reports data, Favarò et. al. analyzed and provided a comprehensive overview of disengagements data provided by the autonomous vehicle manufacturers from their testing on California public roads from 2014 and 2017 to comprehend the safety-critical role of autonomous vehicle disengagement as it requires the control of the vehicle to transferred to the human driver in a safe and timely manner [7]. Authors presented trends in reporting disengagements, preliminary estimations of disengagement frequencies, average mileage driven before failure and disengagement and an examination of triggers, reported contributory factors and causes of the disengagements with the aim of highlighting limitations of the current regulations [7].

To understand the interactions of autonomous vehicles and conventional vehicles driven by human drivers, Boggs et. al. conducted a text analysis of the crash report narratives from the 124 collision reports and analyzed injury and rear-end crashes in a full Bayesian setup and estimated hierarchical-Bayes fixed and random parameter logit models for each crash type [2]. Their results revealed that the likeliness of rear-end crashes involving autonomous vehicles when automated driving system was engaged was substantially higher as opposed to the vehicle where automated driving system was disengaged prior to crash or autonomous vehicle was being driven by human driver [2]. They reported 13.3% injury crashes associated with autonomous vehicles and 61.1% rear-end collisions [2]. As far as the tendency of injury crash involving autonomous vehicle was concerned, a significantly positive statistical correlation between the speed at which conventional vehicle was travelling and injury crash tendency was revealed with a lower likeliness of injury crash involving autonomous vehicle at roadways with marked centerlines [2]. Moreover, clear weather conditions were also found to be associated with a lower likeliness of injury crash tendency involving autonomous vehicles [2]. Another study analyzed crash narratives from the collision reports to identify and understand safety concerns and gaps between crash types during transferring of controls between automation and human drivers and automation interactions on roadways [2]. Authors used probabilistic topic modeling of open-ended crash narratives to analyze the crash database and identified five themes viz. sideswipe crashes during overtakes from left side, transition crashes initiated by the driver, rear-end collisions that happened when vehicle was stopped at an intersection, in turn lane, and when crash involved oncoming traffic [2]. They discovered that a significant number of crashes associated with side swipe collisions involved motorcycles and were also represented by transitions initiated by the driver [2]. Their findings highlighted formerly raised safety concerns with transitions of control by the driver and interactions between vehicles in automated mode and social network of transportation [2].

Wang and Li investigated the autonomous vehicle crash reports from 2014 to 2018 using statistical modeling approaches which involved both classification and regression trees (CART) algorithm for classification tree and ordinal logistic regression with the goal of statistically analyzing and understanding autonomous vehicles' safety issues [10]. They explored the mechanism of crashes related to autonomous vehicles through perspectives of collision types and crash severity by performing a quantitative analysis using these modeling approaches [10]. With the help of CART model, they revealed and visualized the hierarchical structure of the autonomous vehicle crash mechanism while understanding the contribution of roadway, traffic, and environmental factors in causing crashes of different severities and collision types [10]. The results of the statistical analysis indicated a significant increase of crash severity when autonomous vehicle is responsible for the crash. Authors also identified highway to be the primary location where severe injuries most likely happen and the fact that vehicle operation in autonomous mode, crashes involving pedestrians/cyclists and roadway environment affects autonomous vehicle collision types [10].

Das et. al. collected scanned collision reports filed by different manufacturers from September 2014 and May 2019 to study factors that contribute to autonomous vehicle collisions, in order to understand and identify risk safety factors related to autonomous vehicle collisions [5]. They performed a comprehensive analysis of critical variables to demonstrate a variational inference algorithm for Bayesian latent class models and applied clustering algorithm to the collision data. The Bayesian latent class model that they used identified six classes based on collision characteristics [5]. The variables they used based on collision traits included type of collision, vehicle damage, severity of operator injury, number of vehicles involved in collision, lighting conditions and weather conditions, whether the vehicle was stopped or moving, and the events before the collision. Their results illustrated a higher percentage of injury severity level linked to the classes associated with multi-vehicle collisions, turning, dark lighting conditions with street-lights, rear-end collisions and side swipe [5]. Another finding was a high probability of occurrence of adverse weather collisions when the vehicle was operating in autonomous mode and its previous driving condition was stopped [5].

Gaps in literature in terms of converting the collision data pdf reports into csv file (see Appendix figure B9 for screen capture of the CSV data file) to extract meaningful structured data; classifying, labelling and evaluating it, and developing a linear sequential ANN model to produce valuable information has been fulfilled by this dissertation.

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CHAPTER 3. TRUST AND SECURITY IN INTELLIGENT AUTONOMOUS SYSTEMS[1]

3.1. Abstract

Autonomy is defined in terms of the degree of capability of a system or machine to function without human intervention. Degrees of autonomy can vary from requiring fully engaged human involvement at one extreme to having none at the other extreme. Levels of trust on the part of humans concerns the extent of belief or confidence in the system. When a system with some degree of autonomy makes decisions and carries out its functions, trust in the system may rise or fall in accordance with perceptions or measurements of the system performance. Measurement of trust is typically related to ethical, moral, social and legal norms of society, along with metrics related to taking responsibility. Trust is related to cybersecurity in that insecure systems inherently have low trust. The work of this paper surveys and explores concepts of trust in terms of relationships between humans and systems. An ontology that characterizes this relationship is provided. Trust issues as they pertain to the areas of cybersecurity and autonomy are characterized. The concept of anti-autonomy and counter measures that apply to autonomous weapon systems is also included.

Key Words: Autonomy, security, trust, intentionality, semi-autonomy, anti-autonomy, vulnerabilities, human-in-the-loop, and human-on-the-loop.

3.2. Introduction

Advances in the use of Artificial Intelligence (AI) in autonomous systems is revolutionizing decision making in society. Human-centric decisions have long been the norm in many application domains such as medical diagnosis, financial operations, driving cars, flying

[1] The material in this chapter was co-authored by Aakanksha Rastogi and Kendall Nygard. Aakanksha Rastogi is the primary author responsible for actual contributions and research work illustrated in this journal article. Aakanksha Rastogi was the primary developer of the conclusions that are advanced here. Aakanksha Rastogi also drafted and revised all versions of this chapter. Kendall Nygard advised on the background literature and helped with editing the document.

airplanes, and legal case research. However, in many domains, at a fast rate of change, humans are relinquishing decision making to autonomous systems that have intelligent capabilities. The quest for fully autonomous self-driving cars is a good example of machines undergoing a steady march toward increasing levels of autonomy and intelligence over time. Anti-lock brakes are now an old technology, but for many years some drivers viewed them with fear and regarded them as an inappropriate encroachment on driver control. More recently, some new cars are equipped with lane following assist technology, which automatically does things like keeping the vehicle in a lane, maintaining offset distances, accelerating, braking, etc. At some point self-driving cars may be fully autonomous. Many cyber-physical systems are heavily equipped with sensors, actuators, and controllers, but unlike earlier generation machines, in the march toward intelligent autonomy, also involve integrated symbolic or sub-symbolic AI to do their work.

When systems with some level of autonomous operation deviate from their expected behavior in negative ways, humans tend to decrease their level of trust in intelligent machine performance. In the other direction, it can also be true that repeated positive performance can incrementally increase a trust level. In some cases, autonomy is adjustable, and the machine itself may call for human intervention. For example, some robots are programmed to request human intervention under certain circumstances.

By definition, autonomous systems are capable of changing their behavior in response to unanticipated events during operations [41]. According to Hancock, “autonomous systems are generative and learn, evolve and permanently change their functional capacities as a result of the input of operational and contextual information. Their actions necessarily become more indeterminate across time” [16]. They can decide for themselves what to do and when to do it [13]. These systems can achieve their assigned goals by constructing and executing a plan without requiring any human intervention even in the face of unexpected events [45]. They can be deployed in remote environments where direct human control is not feasible or in environments that are hostile and dangerous to humans [13]. When compared to human-centric systems, some autonomous systems can have advantages of providing faster response times at lower cost. In addition, autonomous systems may not require as much training and monitoring as people often do. People also need things like medical support, guaranteed safe environments, and legal oversights. Most autonomous systems have a decision-making agent that is responsible for making decisions that simulate the human mind. Machine learning has opened new possibilities for systems to become intelligent enough to autonomously operate under widely varied circumstances with minimal or no human intervention. In a broad sense, such capabilities explain much of the rise of artificial intelligence (AI) in our society.

In some cases, systems may be semi-autonomous systems inherently requiring human intervention to be successful in completing certain tasks. Even though inter-device communication may play a role, these systems require human operators to control higher levels of decision making [45]. Zilberstein refers to semi-autonomous systems as "systems that can operate autonomously under some conditions but cannot always complete an entire task as their own" [45]. Semi-autonomous systems can be classified as of SAS-I type if their planning process does not take human intervention into consideration. SAS-II types have planning processes that include knowledge of human intervention into consideration [45]. To coordinate with semi-autonomous systems, it is often important that they are aware of human interventions and can recognize the conditions under which autonomous actions cannot solely perform the operation to complete the tasks without human input. Moreover, humans must be thorough and precise with the decision-making processes and AI protocols with which these systems are equipped. This paper addresses key questions, understanding, and clarification of human-machine relationships.

The paper is organized as follows. Section 3.3 describes the concepts of trust in autonomous systems. Section 3.4 describes human interfaces with autonomous systems. Section 3.5 describes the measurement of trust in autonomous systems related to cybersecurity. Section 3.6 describes the understanding of the concept of anti-autonomy. Within Section 3.6 concerning drones, a description of counter measures or anti-drone technologies that help avert potential collateral damage and casualties caused by autonomous weapon systems is given. Section 3.7 describes the relation of security with autonomy. Section 3.8 provides conclusions.

3.3. Trusting Autonomous Systems

Humans have created intelligent machines and systems using AI protocols and advanced machine learning concepts and techniques. When the singularity occurs, intelligent machines are expected to create ever more intelligent machines, triggering an unrelenting escalation. Autonomous systems that use advanced AI techniques have shown improvements in deception and the use of experience, interventions, and control. With these changes in the nature of autonomous functionalities, trusting these systems has become more complex and challenging. In defining trust, there are often references to attitudes, beliefs, intentions, and behaviors. In the many definitions of trust offered, there is typically reference to expectations regarding outcomes or behaviors [28]. Specific to automation, trust can be described as “the attitude that an agent will help achieve an individual’s goal in a situation characterized by uncertainty and vulnerability” [28]. Dutta et. al. defined trust in an autonomous system as “the ability of the system to successfully carry out a task, at a particular time, and in a situation characterized by vulnerability and uncertainty” [11].

Trust among humans and between human and automation are fundamentally different due to a lack of intentionality in autonomous systems [28]. Since human-centered trust is related to concepts of benevolence, value congruence and loyalty, human-automation trust presents difficulties concerning purpose [28]. Lee and See pointed out that trust between people is a part of a social exchange relationship which makes trust between humans different from trust in automation [28]. There is also a lack of symmetry (where trustor and trustee are aware of behavior, intents, and trust of others) between humans and machines [28]. Trust in automation is an attribution process whereby trust can be derived from direct observation of behaviors (performance), an understanding of the underlying mechanisms (process), or from the intended use of a system. Trust is an important mediator of relationship between humans and automation. Choi and Ji described trust to be a major determinant of reliance on and acceptance of automation, standing between people's beliefs toward automation and their intention to use it [4]. For instance, while investigating the importance of trust while adopting autonomous vehicles, the following dimensions are prominent: 1) transparency, for understanding and predicting vehicle operations, 2) technical competence, for perceiving vehicle performance, and 3) situation management, for confidence in the vehicle adaptively maintaining control in an unanticipated situation [4]. Anthropomorphism, which is attributing human characteristics to a nonhuman entity, can be an important determinant of trust [42]. Anthropomorphism can be viewed as a process of inductive inference, particularly concerning capacity for rational thought or agency and conscious feeling [42]. Trust is a multifaceted concept that refers to a belief in another behaving with integrity, benevolence, predictability or competence, a prediction of anthropomorphism increases confidence and trust [42]. To establish an assertion that anthropomorphism affects user trust, an experiment was conducted in which participants using a National Advanced Driving Simulator were instrumented for psychological assessment and randomly assigned to degrees of autonomy corresponding to normal, agentic, and anthropomorphic driving conditions. Human voices and gender information were a part of the anthropomorphic features [17] [42]. In terms of overall trust, participants who drove their vehicle in anthropomorphic condition had the highest trust, followed by Agentic, then by Normal [42]. This established statistically that the degree of anthropomorphism mediated the relationship between the vehicle condition and overall trust in the vehicle. These findings strengthen the concept that trust is related to perceptions of human mental capacities. Similar results on the effectiveness in the elicitation of positive perceptions of the agent upon introducing humanlike appearance and high autonomy in self-driving cars have also been reported. Additionally, mediation analyses revealed that the introduction of humanlike appearance and high autonomy induced by greater levels of anthropomorphism introduced feelings of social presence which imposed a positive impact on perceived intelligence, safety, and trust in the agent. This suggests that feelings of social presence during interaction with an agent is a determinant of the extent to which users perceive a driving agent as safe, trustworthy, and intelligent [27]. Even when automation is limited but anthropomorphism is high, an elevated feeling of trust and safety followed and resulted in positive perceptions of the system [26].

The concept of trust is somewhat elusive in the sense that intentionality, purpose, belief and reputation play a role, but so do credibility, consciousness, empathy, sympathy and responsibility. Correlations and relationships of these concepts with trust takes on importance when we analyze human-machine relationships. Again, in the self-driving car example, all of these concepts are in the minds of people when they consider peace of mind when riding in such a car and influence the level of trust a person has that the vehicle will safely and efficiently get them to their destination. One factor that influences the level of trust that a person has in any vehicle even if a driver is in control concerns the possibility of encountering unforeseen situations and the need to react appropriately and safely. Examples include encountering drunken drivers, construction zones, or a vehicle failure such as a tire spontaneously going flat. If software is handling such situations, there are serious questions about updates, such as how effective and how frequently they are done to account for new information. Apart from self-driving cars, robots and robotic humanoid assistants must deal with similar problems.

If data-centric machine learning methodologies are used for intelligent training, the ever-present issues surrounding the appropriateness and completeness of the data that is employed are encountered. In addition, there is a significant challenge that lies in supporting consciousness in a machine, and the attendant need for the machine to be fully aware and have an understanding of the human ways of doing things and reacting to their own stimuli as they conduct their activities. Seamlessly merging such machines into our daily lives as people will require these kinds of capabilities. It is also the case that humans are far from infallible. Every person has made decisions for which they thought twice or multiple times, agonized over whether they made the right decision, or wished that they had been able to predict unforeseen consequences. Advanced sensors, massive data sets, and rapid communication capabilities have resulted in great strides in machine awareness. Given that awareness is only one necessary ingredient of trust, and that trust is a key component of responsibility, it is clear that developing truly responsible machines is still in the future. Research concerning interactions among humans has established that high levels of trust drive responsible behaviors. This suggests that there is potential to build responsible systems whose behavior sympathetically and empathetically complement our expectations.

It is widely held that autonomous systems lack human emotions such as happiness, sadness, fear, anger, surprise and disgust. The concept of empathy concerns awareness and sensitivity to the feelings and thoughts of another, even if not fully communicated in an objectively explicit manner [8]. Empathy is often thought of as a vicarious experiencing of those feelings and thoughts of the other person. The related concept of sympathy is an affinity, association, or relationship between persons or things wherein whatever affects one similarly affects the other [7]. Robotic humanoid assistants can use speech recognition software to mimic human emotions. Software uses digitally converted speech waves as parameters, turns them into words and then uses a semantic decoder to convert words into meaning. Though there has been significant research into developing socially and emotionally adept robots with the help of speech recognition software, the software still makes mistakes, which can leave these robots with failures to understand human intent and emotions [14].

Trusting autonomous systems and delegating tasks to them to gain realization of their full values also requires a belief that these systems are going to be truly effective [33]. Once these systems are trusted, delegated tasks that are then fulfilled can help reduce associated personnel costs and improve safety. Developers who program the AI engines of autonomous systems can focus on providing the ability to carry out complex tasks, which can help to minimize the number of people tied to operations, resulting in money saved [33]. When the level of autonomy in weapon systems is increased there are improvements in war fighting capabilities while reducing the need for human operators [24]. However, the high level of autonomy in such systems in using advanced algorithms to detect targets and deploy attacks comes with major trust issues. Groups such as Human Rights Watch are constantly attentive to the issue and promote negotiations to impose preemptive bans on the development, production, and usage of fully autonomous weapons on the battlefields. Once deployed, autonomous weapons can be difficult to recall if a scenario changes, new information is obtained, or there is misidentification of a target [24]. The infamous 1991 failure of a Patriot missile system to track and intercept an incoming Scud missile resulted in the deaths of 28 soldiers and was caused by a subtle programming error.

3.4. Humans Interfacing with Autonomous Systems

Partial, sliding and semi–autonomous systems often require humans to interface with them during their operations. This introduces the concepts of human-in-the-loop and human-on-the-loop [31]. Human-in-the-loop (HITL) or semiautonomous robotic systems (RAS) autonomously perform a task for a certain time, then pause and wait for commands from a human operator before continuing. For instance, in autonomy used by HITL autonomous systems for searching, detecting, and evaluating threats; selection and engaging of targets are controlled and decided by humans. Human-on-the-loop (HOTL) systems can execute a task fully and independently but have a human in a monitoring or supervisory role, with an ability to intervene if the system fails or if an error condition arises. They are capable of being fully autonomous in performing an entire function on their own if allowed by their human supervisors. By keeping a human-on-the-loop, a need for interactive human and system interfaces is eliminated. However, deadly outcomes can occur. An example is the recent similar crashes of Boeing 737 Max aircraft in Indonesia and Ethiopia that killed 346 people. The trigger of the crashes was the failure of a sensor intended to accurately report the attack angle of the aircraft. Each aircraft was equipped with an autonomous system called the Maneuvering Characteristics Augmentation System, or MCAS, which is intended to use sensor input and autonomously take corrective action that down points the nose of the aircraft if it is about to stall. In each case, when the human pilot intervened, the MCAS system reacted by again initiating the down pointing action. Back and forth interactions of the automated system with pilot corrective action meant that eventually the multiple down pointing actions resulted in a crash known in the industry as uncontrolled flight into terrain. Many pilots have expressed frustration at being caught off guard by automated sudden descents of the aircraft. In the autonomy employed by HOTL weapons systems, RAS systems select and engage targets that were not decided upon by human supervisors. Humans can monitor the intention and performance of the weapon system and can cancel, interfere, or stop its operations if necessary. Applications where humans use supervisory control to directly control the system either involves an autonomously running process where human intervention includes a control algorithm which adjusts set points whenever necessary; or a process accepting a command, carrying it out autonomously, reporting results and waiting to receive further commands from the human [30].

A human who has an in-depth knowledge and understanding of technical details of code, algorithms, functionality, and behavior of a machine he/she is operating can better handle critical situations while averting or overriding machine decisions and taking control. This raises a concern as to how a situation should be dealt with when, for example, an autonomous vehicle is compromised by a malicious user while a non-technical human was interfacing with the vehicle. Little research has addressed this kind of question, which results in attack vulnerabilities. Predicting human behaviors in unavoidable situations is difficult given that autonomous systems are typically preprogrammed to not make choices that can be construed as dangerous [9]. Extending system modelling techniques to capture human behavior is extremely difficult due to complex psychological, physiological, and behavioral aspects of human beings.

3.5. Measuring Trust in Autonomous Systems

Trust assessment, measurement, and management require a thorough understanding of the concept of trust, often uncovering degrees of, and multi-dimensional nature of trust. Trust management concerns collecting, analyzing, and presenting trust related evidence and making assessments and decisions regarding trust relationships between entities in a network [22].

Measuring trust relies upon quantitative values for traits such as reliability, competence, security vulnerabilities and robustness as well as transparency of control. Trust assessment is furthered when these factors are measured in uncertain and certain environments [11].

As autonomous systems become more complex, instability and uncertainty in workplace situations can increase due to increased cognitive complexity [32]. Accompanying feelings can be unsettling to people. When comprehension of an intricate automation system becomes difficult or impossible, high levels of trust are helpful in coping with uncertainty, particularly when situations are dynamically changing and there is little basis for decision making or means of exercising control by humans who are in or on the loop. The degree of trust influences the performance of the systems and affects acceptance and reliance on automation, along with the strategies that operators use during automation. Hence, measurement of situations of trust and mistrust are necessary in predicting system performance [32]. One example of the cognitive process is illustrated by work of Oh et al. [32] analyses in which electroencephalograms (EEGs) were used to measure brainwaves in situations that involved trust and mistrust. Trust levels were found to be associated with effective decision-making and performance elevation through measurable increases in concentration. When mistrust was evident, stress and anxiety interrupted and was inimical to effective decision-making. A study by Wang et al. [40] used EEG signals and facial images to establish that human identity is important is assessing trust and assurance and drives effective human-machine interaction. In a tie-in with the Software Development Life Cycle, the study in [18] asserts that human trust in autonomy can be achieved by applying formal methods. Basically, a formal model of the autonomy software can help to verify that critical properties such as safety and service are in place, providing assurance that an autonomous system will satisfy requirements. As trust applies to autonomous vehicles, formal methods in conjunction with simulations and employing the Software Cost Reduction (SCR) toolset have been used to establish elevated levels of trust [18].

Another method of measuring trust in self-driving cars was described in [19]. The approach uses gaze behavior and eye-tracking in a visually demanding nondriving-related task during highly automated driving. Situational, dispositional, and learned automation settings were configured, and trust levels were self-reported. Associations between gaze behaviors and the level of trust in the automation were established. The work sets the stage for further studies in which trust is evaluated by quantitative methods apart from self-reporting. There is an advantage in being non-invasive. In a further study a real-time sensing of trust levels was based upon an innovative model that maps psychophysiological measurements of human trust levels into human-machine interactions [20]. Finally, in the domain of self-driving cars, aircraft, and pharmaceuticals, trust levels can be derived from standards utilized by regulatory bodies that provide certifications for safety and reliability of safety-critical technologies that are employed [9].

3.6. Anti-Autonomy

When the integrity, behaviors and functionalities of an autonomous system is compromised in an attack, not only does it become vulnerable to future attacks, but also becomes a potential source of danger or a threat to other autonomous systems, agents, and humans. Lack of intentionality makes it more difficult for humans to establish trust. A constant concern is that a wrong piece of code can make a system potentially dangerous and capable of wreaking havoc in their surroundings. One such example is the use of autonomous robots on battlefields. Potentially blamed for noncombatant casualties and collateral damages [2, 12], the usage of fully autonomous robotic weapons systems is banned by military operations in the United States. Autonomous weapon systems are accused of violating fundamental human values from an ethical point of view, including the ethical standards established by International Law of War [36]. Since battlefield robots and weapon systems do not experience anger, fear, or frustration in ways that humans do, they potentially pose greater risks towards noncombatants [2]. Similarly, in self-driving cars in situations where decisions must be made as to who is saved and who is killed it poses ethical dilemmas. The fundamental question of how to impart ethical and moral values into such systems arises. This gives rise to the concept of anti-autonomy, which leads to the perplexities of decision making in the event of the behavior of an autonomous system going awry.

Anti-autonomy basically considers how to counter attacks by autonomous systems. The work of Huang and Wicks [21] begins with analysis of attack strategies, then applied to a large-scale distributed intrusion detection framework to address issues of work division, information exchange and coordination among available Intrusion Detection Systems (IDS). One approach employs autonomous local IDS agents to perform event processing coupled with cooperative global problem resolution. The idea is to discern enemy intent as pioneered by Howard and use the framework to drive a basis for how different IDS components work together [21]. It has also been established that cooperation of a single detection system with remote detection systems located in other parts of the network can improve detection performance. The Cooperating Autonomous Detection Systems (CATS) is an instantiation of the approach [10]. A distributed monitoring environment can improve detection results. To increase the availability of the overall systems and to avoid instances of a detection system falling victim to itself, it is important that each subsystem performs attack detection autonomously. Although, detection accuracy may be increased by the intercommunication between subsystems, this is not a pre-requisite for global detection functionality and hence, autonomous behavior of systems should possess self-configuration, self-maintenance, self-healing, and self-optimization capabilities. Intrusion detection approaches using inclusion and distribution of agents on a network-wide basis to monitor the system effectively and efficiently and improve detection has also been reported by Crosbie and Spafford [5, 6].

3.6.1. Automation of Anti-Autonomy

Robots on the battlefield traditionally carry out tasks like detecting and neutralizing improvised explosive devices (IEDs); using sensors to detect hazards like radiation, biological agents, or chemicals; or conducting surveillance. The complexity of what robots are capable of is rapidly increasing. Unmanned Aerial Vehicles (UAVs) or drones are showing the way in terms of technological advancements, including the decision making and deploying of weapons. However, autonomous weapons systems are still largely designed for human-in-the-loop decision making. It is now common for a UAV to support military operations with both onboard weapons and surveillance capacities. Such systems can identify, locate, and eliminate targets in combat zones. Equipped with radar antennas, navigation systems and satellite communication, they can identify, lock study, and attack targets, with weapons dispatched under human control. In some cases, remote operators are working from very distant locations. Newer generations of battlefield weaponry can autonomously assess a battle zone much faster and more thoroughly than a human can and react very quickly if authorized to do so. UAVs are often carrying out missions that include coverage of non-combat zones, increasing the risk of collateral damage to civilian populations, which often raise special social and ethical concerns. Unlike replacing human forces in a battlefield, UAVs that are lost in battle can often easily be replaced with spares. Forecasts indicate that as many as 7 million drones will take flight by the year 2020. This is in contrast to a figure of under 40,000 piloted aircraft in operation today.

Given the enormous investment in technologically advanced UAVs and automated robotic systems, it is natural to consider ways to develop counter measures and protect against automated attacks. Terminology like anti-UAV and anti-drone technologies have entered the military vernacular. Basic approaches focus on detecting and intercepting unmanned aircrafts, with similarities to how Patriot missile systems have functioned for many years. Approximately 235 counter-drone products have been developed by 155 manufactures in 33 countries [29]. Products can be ground-based, hand-held or airborne. Detection strategies include radar, Radio Frequency, Electro-Optical, and Infrared. Interdiction methodologies include GPS spoofing and jamming of tracking systems and communication devices on enemy systems. For anti-drone systems specifically, trade and technology names include DroneGun, Advanced Test High Energy Asset, Laser Weapon Systems, Radar-guided missiles, DroneCatcher, SkyWall, SkyFence, Eagle Power and Drone Malware [35]. Challenges in the design and development of such systems include issues of precision, performance, practicality, detection, tracking and interdiction effectiveness. An example of a complication is that a C-UAS jamming system designed to stop UAV communication can also jam networks in small or commercial airplanes in the vicinity. Electro-optical systems and acoustic sensors have been known to confuse drones with birds or other airplanes. When used near airports, electromagnetic and radio frequency interference can cause air traffic control issues. In addition, many counter-measures are illegal or restricted in certain countries [37].

3.7. Security in Autonomy

Since autonomous systems are potentially threatening to humans, security and privacy issues are of importance, and lapses often require immediate attention and rectification. Hacking of these systems can also cause casualties and collateral damage. When autonomous weapon systems accept and process commands on the battlefield, although intended to respond and act within laws of war and rules of engagement, significant damage can be caused if victimized by hacking attacks [25]. When the software involves complex algorithms and control systems, software testing is often incomplete and vulnerabilities are present, offering invitations to hacking and hijacking. Internet connectivity opens other avenues for hacking. Networks of autonomous systems are supported by the interdomain routing protocol called the Border Gateway Protocol (BGP). Because the dynamic nature of the routing infrastructure that includes competitive, self-interested autonomous nodes, the BGP network is prone to vulnerabilities, failures, communication interruptions and malicious attacks [3, 23]. Multiple approaches have been developed to enhance BGP network security. Pretty good BGP (PGBGP) can detect anomalies and respond, including assessing the minimum number of autonomous systems that are required to adopt a distributed security solution that would provide protection against known exploits [23]. Other secured versions of BGP include secure-origin BGP, secure-BGP and pretty-secure BGP [3]. IP routing infrastructure is susceptible to critical security vulnerabilities and malicious attacks. Shue et. al. [38] found multiple autonomous systems with high concentrations of malicious IP addresses, and others that were disproportionately experienced high malicious activities in comparison with their equivalently sized peers. To determine which internet service providers and autonomous systems reveal high malicious behavior they used 10 blacklists, extensive DNS solutions, and local spam data. The blacklists, exploited hosts, phishing sites, bot command and control and malware downloads were used as inputs. Malicious activities were found among autonomous systems that were peering with other systems on a regular basis [38]. While malicious attacks are frequently launched by botnets, the originating autonomous systems, and the systems with higher degrees of maliciousness resulted in penalizing legitimate traffic on the internet and causing extensive collateral damage.

Vulnerabilities and malicious attacks have reached into the world of autonomous and unmanned vehicles. Most vehicles are equipped with automation features such as satellite navigation, anti-lock braking systems (ABS), cruise control, lane departure assist, moving object detection (MOD) and parking assist, which provide at least semi-autonomous functionalities to these vehicles. The software behind these features are vulnerable to failures caused by cyberattacks, software and hardware anomalies, and defects that have been accidently introduced by the developers [44]. Yağdereli et al. [43, 44] provided a classification of threats and attacks and proposed development guidelines and mitigation strategies to use in the development of autonomous and unmanned vehicle systems [44]. Security of autonomous vehicles has also been discussed by Thing and Wu where they presented a comprehensive taxonomy to categorize security vulnerabilities, threats, attacks, and potential defenses in an autonomous vehicle in order for its infrastructure to be more secure and dependable [39]. To implement the quality, security, and safety during the development of autonomous embedded electronic systems inside autonomous vehicles, Gifei and Salceanu [15] proposed a Quality Safety Cyber Security Integrated Management System (QSCSIMS) which enhances security and safety aspects and also decreases time spent on following standards and associated costs. Autonomy systems are surrounded by security issues, vulnerabilities, and attacks induced by human elements who introduced bugs while programming; by hackers invading systems or implementing complex algorithms that produces self-manifesting bugs.

3.8. Conclusion

This work provides a characterization of trust issues as they pertain to the areas of cybersecurity and intelligent autonomous systems. Self-driving cars and drones are prototypical examples of intelligent autonomous systems that are widely viewed as having positive impacts on human lives. However, such systems have not been completely successful in establishing that humans will fully trust that their behaviors always follow ethical, social, and legal norms of society. For self-driving cars in particular, people express concerns underlying safety, security, and decision-making, especially during critical situations and circumstances. Anthropomorphic characteristics are helpful in elevating trust, especially in robotic humanoid assistants. There is substantial technical progress in making these types of systems more reliable and in modeling and training them to be compliant with human values. Consciousness, empathy, and sympathy are characteristics that are difficult to support in intelligent autonomous systems, yet humans want these characteristics. Battlefield robots and weapon systems are advancing rapidly yet are still largely operated with human-in-the-loop designs. Fully autonomous weapons systems that make strike decisions have not achieved the high level of trust needed for deployment, even in settings where they can be shown to exceed human decision-making performance. As weapons systems exhibit more autonomy, systems to counter them with anti-autonomy designs are becoming more prevalent. It is widely held that one small mishap can translate into disasters with collateral damage and loss of life, including non-combat civilian casualties. Autonomous systems are not limited to physical machines and devices, but also exist throughout the internet in the form of smart software agents and botnets accepting and executing commands. While some of these systems have gained some measure of trust by humans, measurement of trust is hampered by a lack of established standard measurement procedures. In addition, since such systems are developed and programmed by humans, they are prone to security issues, attacks, vulnerabilities, and threats, for which researchers have been exploring intrusion detection techniques, approaches, and methods to avert failures, outsmart hacking attacks, and prevent disasters.

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CHAPTER 4. THREAT AND ALERT ANALYTICS IN AUTONOMOUS VEHICLES[2]

4.1. Abstract

Autonomous vehicles or self-driving cars emerged with a promise to deliver a driving experience that is safe, secure, law-abiding, alleviates traffic congestion and reduces traffic accidents. These self-driving cars predominantly rely on wireless technology, vehicular ad-hoc networks (VANETs) and Vehicle to Vehicle (V2V) networks, Road Side Units (RSUs), Millimeter Wave radars, light detection and ranging (LiDAR), sensors and cameras, etc. Since these vehicles are so dexterous and equipped with such advanced driver assistance technological features, their dexterity invites threats, vulnerabilities, and hacking attacks. This paper aims to understand and study the technology behind these self-driving cars and explore, identify, and address popular threats, vulnerabilities, and hacking attacks to which these cars are prone. This paper also establishes a relationship between these threats, trust, and reliability. An analysis of the alert systems in self-driving cars is also presented.

keywords: Self-driving cars, advanced driver assistance systems, trust, reliability, ethics, security, threats, vulnerabilities

4.2. Introduction

In recent years, human imagination, creativity, artificial intelligence, and a relentless quest to expand dexterity of automobiles has led automobile engineers to design and engineer an automobile that is self-reliant, self-sufficient, and self-driving. Imagining a future where a self-driving car run errands (such as picking up clothes from dry-cleaning) while you are still at work and reaching office just in time to pick you up when you are done, is not a far-fetched dream.

[2] The material in this chapter was co-authored by Aakanksha Rastogi and Kendall Nygard. Aakanksha Rastogi is the primary author responsible for actual contributions and research work illustrated in this article. Aakanksha Rastogi was the primary developer of the conclusions that are advanced here. Aakanksha Rastogi also drafted and revised all versions of this chapter. Kendall Nygard helped with editing the document.

Automobile industries are already on a haul to launch their self-driving cars while still competing amongst themselves towards constantly improving their cars. While attempting to design a self-driving car that is fully autonomous, they perform rigorous testing of their vehicles and prepare them for adverse road conditions, simulate driving conditions and environments. Waymo self-driving cars have claimed to have been driven for over 8 million miles on road, averaging about 25,000 miles per day, and over 5 billion miles in simulation. However, with all the testing techniques these engineers employ in making these self-driving cars to ensure their safety, security and minimally risky, employing ethics into these cars is still a bigger concern. Ethics relates to morality, conscience, self-awareness, and responsibility which are an integral part of humans/drivers. These qualities are self-learned and cannot be leveraged to train a self-driving car into taking ethical decisions while encountering adverse situations on the road. Despite the efforts put together in incorporating ethical decision making systems, there are still several examples of countless situations, circumstances and driving conditions where ethical systems of self-driving cars can be challenged. Trappl brought up the concept of utilitarianism and cited several such scenarios which arguably questioned the ethical decision making capabilities of self-driving cars [24]. To which, Borenstein et. al. sought to discuss the ethical responsibilities of hardware and software design engineers throughout the process of design, development and testing of autonomous or self-driving cars and that each designer is ethically obligated towards creating safer technology [4]. Yet another thought-provoking concern is factoring in driver's stress levels while encountering challenging situations on the road. For instance, a situation where a bus driver driving on a slippery road encounters a deer jumping right in front of the bus. In this case, the bus driver could end up slowing the bus just enough to let the deer pass while trying not to skid or ending up killing the deer just for the sake of saving the lives of the passengers. Irrespective of the decision the bus driver takes, he can still be excused in lieu of the stressful situation he/she was in. Self-driving car/bus, on the contrary, would not be excused for any decision it makes since it lacks creativity and ethical decision making capabilities, like human drivers do.

Autonomous vehicles or self-driving cars and semi-autonomous cars are equipped with advanced technology and driver assistance features enabling safe and easier driving experience that abides by the law, rules and regulations and alleviate traffic congestion. However, since these features leverage wireless network, sensors, and cameras, it also opens windows to threats, vulnerabilities and hacking attacks. This paper aims to understand and study technology behind self-driving cars and explore, identify, and address threats, vulnerabilities, and hacking attacks that these vehicles are exposed to. This paper also establishes a relationship between these threats, trust, and reliability. An analysis of the alert systems in self-driving cars is also presented.

The rest of the paper is organized as follows. Section 4.3 identifies the underlying threats to self-driving cars. Section 4.4 presents the strategies availed to mitigate and address these threats. Section 4.5 relates these underlying threats, their mitigation strategies, and resolutions to the concepts of overall trust and reliability in autonomous systems. Section 4.6 provides analytics on the alert-systems in self-driving cars. Section 4.7 concludes this chapter.

4.3. Identifying Threats

Almost every car on the road today comes with advanced semi-autonomous features such as infotainment system (provides vehicle information and entertainment), Traffic Jam Assist in BMW or Traffic Jam pilot in Audi (coordinates live traffic information with satellites and provides alternate routes using car's navigation system), adaptive cruise control (automatically intervenes brakes when needed to maintain safe driving distance with other cars while driving in cruise control mode), self-parking and lane centering steering, Drive Pilot in Mercedes Benz or Autopilot in Tesla (where the driver can keep their hands off the steering wheel and car can lock lane markings and drive itself within the lanes for up to 30 seconds), etc. The basic underlying principle for engineering and managing these semi-autonomous features in these cars is by configuring car's own computers that has car's operating system software which works behind the scenes collaborating with car's electronics, mechanics, power train, wiring, ignition, chassis, etc. Since, these car computers are code behind the scenes, it exposes all semi-autonomous features of the cars to threats and vulnerabilities. It makes these cars prone to hacking attacks. A car's infotainment system can be hacked to gain access to any unit or component inside the car such as ignition, brakes, drive-train, steering wheel, audio/video systems, parking cameras, door locks, wiper blades, etc., allowing hackers to take full control over the car and wreak havoc while the car is still in operation on the road. This can result in highway mayhems, destruction and casualties. Moreover, almost every car has capabilities to sync driver's phone with car's software system via Bluetooth or WiFi which further opens doors to countless attack strategies. Furthermore, Bluetooth, Remote key entry, On-Board Diagnostics (OBD), Dedicated Short Range Communications (DSRC), USB, ABS, sensors [8] and Automobile applications also serve as attack entry points for hackers [9]. Presence of several car hacking demonstration videos and tutorials on the internet second the fact that incorporation of semi-autonomous features aiding car's futuristic appeal is indeed also opening doors to new attack strategies and techniques that can be employed to hack these cars. This can cause destruction to the car itself, the people travelling in it and others sharing the road. Many automobile industries understand and acknowledge these cybersecurity vulnerabilities and threats and even employ white-hat hackers to discover security vulnerabilities in vehicle software. However, with ever increasing technological features being launched in these vehicles, it gets harder to keep up with these security vulnerabilities and address them just in time.

In July 2015, two cybersecurity researchers Charlie Miller and Chris Valasek used their hacking skills to remotely hack into Jeep Cherokee's electrical systems and gained wireless control of the vehicle's computer. They wirelessly accessed the entertainment system which enabled them to send commands to steering wheel, brakes, transmission, and other dashboard functions and killed the Jeep on the highway. According to them, Chrysler's vehicles are designed in such a way that their computer networks and electrical systems behave like smartphones being connected to the internet. This opens them to vast variety to vulnerabilities since these car computers can then be wirelessly hacked as they are already connected to the internet via driver's mobile network Wi-Fi hotspot. After successfully hacking the vehicle, they concluded the factors that hackers use to determine the vulnerabilities of vehicles. These included the types and number of radio devices that connect the vehicle's computer systems to the Internet, whether vehicle's critical driving systems were properly isolated from vehicle's on-board computers and, whether the actions of the cyber-physical components could be triggered by digital commands.

The following month, another hacking demonstration was made by the researchers from the University of California at San Diego. The hackers used a small gadget that is placed on the vehicle's dashboard by the insurance firms to monitor location, speed and efficiency of the vehicle. They used this gadget which was connected to Corvette's dashboard to send carefully crafted SMS messages for transmitting commands to the Controller Area Network (CAN) bus of the car and turned on the windshield wipers and even enabled/disabled its brakes. Another hacking threat was reported on Tesla Model X during summer of 2017 where some Chinese researchers managed to remotely hack Model X's brakes while simultaneously opening the doors and the trunk and timed the blinking of lights to the music streaming from vehicle's audio system. This led Tesla to send out security updates to all of it Model X cars.

As these vehicles are gradually progressing from semi-autonomy towards complete autonomy, hacking threats and vulnerabilities become more of a priority than ever. However, it is still a question as to who would be to blame in the even that a self-driving car goes rogue on the road while driving since it was remotely hacked and causes accidents.

4.4. Addressing Threats

Autonomous vehicles (self-driving cars) and semi-autonomous vehicles (cars with some self-driving features) rely on external communication systems such as Vehicular Ad hoc Networks (VANETs) to exchange control data and sensitive information with road side units. As previously mentioned, autonomous and semi-autonomous vehicles are prone to wireless hacking attacks since their advanced driving features are connected over the wireless network, making them more vulnerable and prone to remote hacking attacks. To ensure the success of technology based on security of networks of these vehicles, they are equipped with VANETs. However, certain characteristics of VANETs exposes these vehicles to threats and vulnerabilities at all their communication layers and cause security issues such as high dynamic topology, speed of the car, mobility, open medium wireless communication, and absence of a fixed security system [1][2]. This leads hackers and intruders to plant their attack strategies and taking control of these cars remotely over wireless network. In a quest to protect the external network of autonomous and semi-autonomous vehicles from attacks such as Denial of Service (DoS), Black hole, Grey hole and Sybil attacks [1][2], Alheeti and McDonald-Maiser proposed an intrusion detection system that is based on Integrated Circuit Metric technology [1][2]. Their detection system called, ICMetric-IDS was based on features generated from bias values of magnetometer sensors and the features extracted from the trace files generated using network simulator [1][2]. Their proposed scheme was able to demonstrate an efficient detection of malicious behavior in external communication of autonomous and semi-autonomous vehicles [1][2].

Apart from being connected to the network, these vehicles also heavily rely on sensors and cameras to support several advanced driver assistance features. This opens doors to another variety of attacks involving sensors and cameras. Sensors and cameras of these cars can be hacked to gain control of the advanced features such as blind spot detection, lane departure assistance, moving object detection, parking sensors and cameras, to name a few. Hence, it is important to carefully consider technical and security aspects of each component that is used during the manufacturing of these cars.

Multiple types of threats, vulnerabilities and attacks have been investigated and described in the literature. Several detection and defense mechanisms have been developed. These attacks, threats and vulnerabilities are categorized in terms of types of attacks and their detection and defense as listed in Table 1.

Table 1: List of Threats/Vulnerabilities/Attacks with Their Detection/Defense

Type of Attack	Attacks/Threats/Vulnerabilities	Detection and Defense
Cyber attack	Sybil attack [18] [22]	Social Graph-based Sybil detection (SGSD) (includes Social Network-Based Sybil Defense, Social Community-Based Sybil Detection) [19], SybilGuard [19], SybilLimit [19], SumUp [19], GateKeeper [19], SybilDefender [19], SybilShield [19], VoteTrust [19], Behavior Classification-based Sybil detection (BCSD) [19], Mobile Sybil detection (includes Friend Relationship-Based Sybil Detection, Cryptography-Based Mobile Sybil Detection [19], Feature-Based Mobile Sybil Detection) [19], Intelligent Intrusion Detection System (IDS) [18] [22], IDS using Deep Neural Network [20], IDS using Outlier Detection [21], Over-the-Air (OTA) updates [25] [25], Ericsson Connection Vehicle Cloud (CVC) system [25] , layer-based solution [25], signature based IDS and anomaly based IDS [26]
Cyber attack	Black hole attack [18] [22]	Intelligent Intrusion Detection System (IDS) [18] [22], IDS using Deep Neural Network [20] , IDS using Outlier Detection [21], Over-the-Air (OTA) updates [25], Ericsson Connection Vehicle Cloud (CVC) system [25] , layer-based solution [25], signature based IDS and anomaly based IDS [26]
Cyber attack	Worm hole attack [18] [22]	Intelligent Intrusion Detection System (IDS) [18] [22], IDS using Deep Neural Network [20], IDS using Outlier Detection [21], Over-the-Air (OTA) updates [25], Ericsson Connection Vehicle Cloud (CVC) system [25] , layer-based solution [25], signature based IDS and anomaly based IDS [26]
Cyber attack	Grey hole attack [18] [22]	Intelligent Intrusion Detection System (IDS) [18] [22], IDS using Deep Neural Network [20] , IDS using Outlier Detection [21], Over-the-Air (OTA) updates [25], Ericsson Connection Vehicle Cloud (CVC) system [25], layer-based solution [25], signature based IDS and anomaly based IDS [26]
Cyber attack	Denial of Service (DoS) attack [18] [22]	Intelligent Intrusion Detection System (IDS) [18] [22], IDS using Deep Neural Network [20] , IDS using Outlier Detection [21], authentication [24],revocation [24], Over-the-Air (OTA) updates [25], Ericsson Connection Vehicle Cloud (CVC) system [25] , layer-based solution [25], signature based IDS and anomaly based IDS [26]
Cyber attack	Distributed Denial of Service (DDoS) attack [18] [22]	Intelligent Intrusion Detection System (IDS) [18] [22], IDS using Deep Neural Network [20], IDS using Outlier Detection [21], Over-the-Air (OTA) updates [25], Ericsson Connection Vehicle Cloud (CVC) system [25] , layer-based solution [25] , signature based IDS and anomaly based IDS [26]
Cyber attack	GPS spoofing [24]	Authentication [24], Over-the-Air (OTA) updates [25], Ericsson Connection Vehicle Cloud (CVC) system [25], layer-based solution [25], signature based IDS and anomaly based IDS [26]
Cyber attack	GPS jamming [24]	Anti-Jam GPS techniques, high quality inertial measurement units [24], Over-the-Air (OTA) updates [25], Ericsson Connection Vehicle Cloud (CVC) system [25], layer-based solution [25], signature based IDS and anomaly based IDS [26]
Cyber attack	Malware attack [25]	Over-the-Air (OTA) updates [25], Ericsson Connection Vehicle Cloud (CVC) system [25], layer-based solution [25], signature based IDS and anomaly based IDS [26]
Sensor attack	Jamming [23]	Ultrasonic MIMO system [23], attack detection system [23], logic check [23], adding randomness to control parameters [23], confidence priority [23]
Sensor attack	Spoofing [23]	Ultrasonic MIMO system [23], attack detection system [23], logic check [23], adding randomness to control parameters [23], confidence priority [23]
Sensor attack	Acoustic Quieting [23]	Ultrasonic MIMO system [23], attack detection system [23], logic check [23], adding randomness to control parameters [23], confidence priority [23], spectrum analysis [24], other source of data such as radar or lidar [24]
Sensor attack	Relay Attack [23]	Ultrasonic MIMO system [23], attack detection system [23], logic check [23], adding randomness to control parameters [23], confidence priority [23]
Camera attack	Attacking Cameras [23]	Ultrasonic MIMO system [23], attack detection system [23], logic check [23], adding randomness to control parameters [23], confidence priority [23]

4.5. Relating Threats with Trust and Reliability in Autonomous Systems

The emergence of self-driving cars started a few years ago with the hopes of achieving full autonomy (level 5 of the levels defined by Society of Automotive Engineers, shown in Table 3). However, in the race to at least get closer full autonomy, manufacturers of popular automobiles, began delivering vehicles with advanced driver assistance systems which brought them closer to level 2 or partial autonomy. These systems were built upon the concepts of artificial intelligence (AI) and machine learning and meant to promise safety of these vehicles on the road. When effectively implemented and thoroughly tested, they hoped to reduce accidents and crashes in turn aiding lesser crash and damage reports to the insurance companies. However, trusting and adopting these autonomous vehicles isn't that easy.

Tussyadiah et. al. conducted a study to investigate how attitude and trust in technology influences the intentions of people to adopt and use self-driving taxi [25]. They conducted a survey with 325 residents and demonstrated that adoption and usage of self-driving taxis is positively influenced by its reliability, functionality and helpfulness and negatively influenced by the perception of technology being dehumanizing [25]. Part of this study with the mention of dehumanizing nature of technology also coincides with the concepts of singularity which is perplexing enough to influence people's trust in self-driving cars. Another study on resistance of users towards radical innovation of self-driving cars showed a psychological barrier of car drivers towards self-driving cars [19]. Several studies have concluded that people are reluctant when it comes to handing over control of their cars to technology because of safety concerns that are caused by fear of system malfunction or potential hacking attacks [12] [13].

Moreover, recently publicized crashes have also questioned the trust and reliability of these self-driving cars. Crash reported in Tempe, Arizona where Uber's self-driving car hit and killed a

49-year-old woman since the system that was supposed to engage emergency stops in dangerous situations was disabled. This led Uber to suspend their self-driving cars. Crashing of Tesla Model S in 2016 also created headlines where the car crashed into an on-coming white truck at the speed of 74 mph killing the car driver. Apart from the actual crash reports and publicity of these self-driving vehicles, other factors such as safety, risk, predictability, trust in engineers that designed the system, technical capabilities of these vehicles and system failures also account for overall user trust and reliance on self-driving vehicles [5].

Even though engineers employ engineering best practices, thoroughly researched and practiced concepts from data mining, machine learning and AI, what they fail to factor in are the social learning skills. Social learning is derived from the terms of responsibility, liability distribution, thresholds of acceptable safety or lines that divide recklessness from negligence that the institutions of society determine [23]. Self-driving cars can only religiously follow the lines of code governing its functionality and operability, but will always fail to apply the knowledge, learning and skills derived from the experiences from complexities and inconsistencies of behaviors of human drivers and pedestrians on the road. Moreover, the lack of standards in the design and implementation of technology behind these self-driving cars, makes it even more difficult for them to operate on the road and survive in the society.

Trust and reliability in self-driving cars also depend on the constantly judging attitude of human drivers in terms of zero-tolerance in the event of mistakes these vehicles are bound to make. Also, the fact that these cars will never be able to predict the behavior of other human drivers on the road, makes it even more difficult to confide in these self-driving cars. Since, there is always so much complex lines of code behind these vehicles that they can accomplish, they are written by a human, and hence are bound to be erroneous and in constant needs of improvement. A possible workaround would be to have designers/developers constantly pushing out software updates to these vehicles wirelessly but determining a set time to push these software updates could be a challenge. Another challenge would be to determine if the updates could be pushed while the vehicle is in motion. Moreover, other than regular software updates to enhance the overall safety of the vehicle, it is also important to consider the security updates which are direly needed to keep up with the hacking attacks, threats, and vulnerabilities these vehicles are prone to.

4.6. Analytics on Alert System in Self-Driving Cars

To ensure the safety of drivers, pedestrians and other vehicles sharing the road, most of the automobile manufacturers are designing cars with advanced driver assistance features, safety features and alert systems. These systems are meant to alert the drivers in the event of unfortunate and unfavorable road conditions. To monitor the alertness of the drivers while driving, automobile manufactures use steering wheel monitors, sensors, and tiny cameras, to name a few. However, these advanced driver assistance features still exist in most of the cars these days as a semi-autonomous addition.

An illustration of these advanced driver assistance systems in cars is presented in Figure 1. A comprehensive list of some popular safety, security, and advanced driver assistance system (ADAS) features are listed in Table 2.

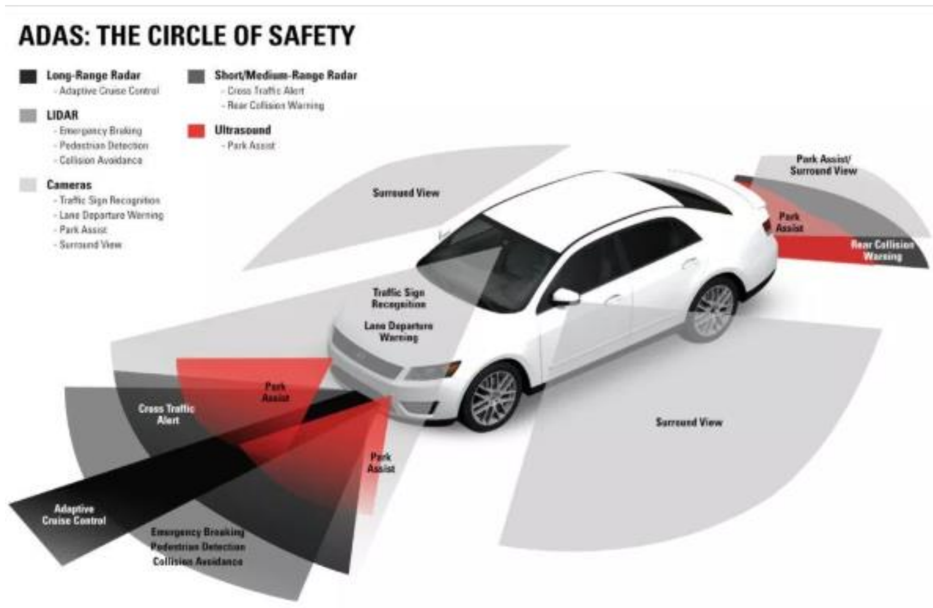

Figure 1: Advanced Driver Assistance Systems (adopted from [8])

Table 2: List of Advanced Driver Assistance Systems (ADAS) (adopted from [5][6][7][8])

ADAS features	Description
Anti-lock braking system	Safety anti-skid braking system
Adaptive Cruise Control	Allows the vehicle to automatically slow down or speed up in response to the speed of the vehicle in front of it
Adaptive Light Control	Controls the headlamps to adjust the lighting in accordance to the natural lighting on the road and illuminate the roads in darkness
Adaptive Lighting	While driving on a darker street, vehicle's headlights are automatically switched to low beam when an oncoming vehicle is passing by and back to high beam when the oncoming vehicle has already passed by
Automatic Braking	Allows the vehicle to intervene and engage brakes automatically to reduce the speed to avert high-speed collisions in the event of driver attention lapse
Automatic Parking	Allows the vehicle to parallel park itself without requiring the driver to do so. Some vehicles park themselves completely while others advice drivers on turning the steering wheel and stopping.
Automatic Crash Notification	Notifies the emergency responders of the crash along with its location
Automatic Emergency Braking	Automatically applies brakes when forward collision is about to happen
Backup Camera	Provides image of the area behind the vehicle and helps prevent back-over crashes
Blind Spot Detection	Allows the vehicles to utilize sensors to help drivers with vital information on moving objects around them
Collision Avoidance Systems	Allows vehicles to utilize sensors to determine vehicle's danger of colliding with another object. In the event of potential collision, system accordingly warns the driver or take preventative actions such as pre-charging brakes, applying tension to the seat belts, adjusting the seats just in time for the airbags to deploy for passenger safety
Crosswind stabilization	Sensors are used to compensate for strong crosswinds
Driver Drowsiness Detection	Allows vehicles to utilize sensors or mini-cameras to determine driver's attention while driving
GPS Navigation	GPS navigation with voice instructions, interactive maps and 3D maps

Table 2: List of Advanced Driver Assistance Systems (ADAS) (adopted from [5][6][7][8]) (continued)

ADAS features	Description
Hands-free steering	Keeps the vehicle in the center of the lane without driver having his/her hands on the steering wheel
Hill Descent Control	Allows vehicle to easily descend steep inclines by automatically activating breaks, the mechanism for which is like anti-lock braking system or traction control system
Intelligent Speed Adaptation	Allows driver to maintain legal speed limit on the road by monitoring the current speed, comparing it to the local speed limit and delivering warnings
Intersection assistant	System monitors cross traffic on an intersection and prompts the driver to apply emergency brakes or automatically engages emergency brakes by activating acoustic and visual warnings
Lane Departure Warning Systems	System uses a variety of sensors to alert the driver while changing lanes.
Lane Keep Assist	If the vehicle is drifting, this system will vibrate the steering wheel or sound an alarm to alert driver to take corrective action to avoid colliding with another vehicle. Some systems even position the car back in its driving lane.
Night Vision	Allows the cars to adjust the brightness of the headlights in several ways including active night vision projecting infrared light or passive night vision relying on the thermal energy from other cars, animals, pedestrians or other objects
Omni-view technology	System turns on the surround and rear cameras allowing the driver to see a 360° view
Parking Sensors	Proximity sensors in the vehicles that alert the driver of the obstacles while parking
Pedestrian Automatic Emergency Braking	System warns the driver of the pedestrian crossing in front of the vehicle or automatically engages brake if the collision is imminent
Rain Sensing	System switches speeds of wiper blades on the windshield depending upon the amount and intensity of rain
Tire Pressure Monitoring	Provides information about inflation level of each tire
Traffic Jam assist	Provides live traffic information during GPS navigation and accordingly suggest alternate routes
Traffic-sign recognition	Recognizes the traffic signs and speed limit signs on the road
Turning assistant	Monitors the oncoming traffic while turning left at low speeds and engages brake in critical situations
Wrong-way driving warning	Emits acoustic and visual warnings in case of signs imposing access restrictions

Figure 2 demonstrates the comparison between number of cars that have key self-driving features over the past 5 years [3][7][15][16][17][18][19][29][22].

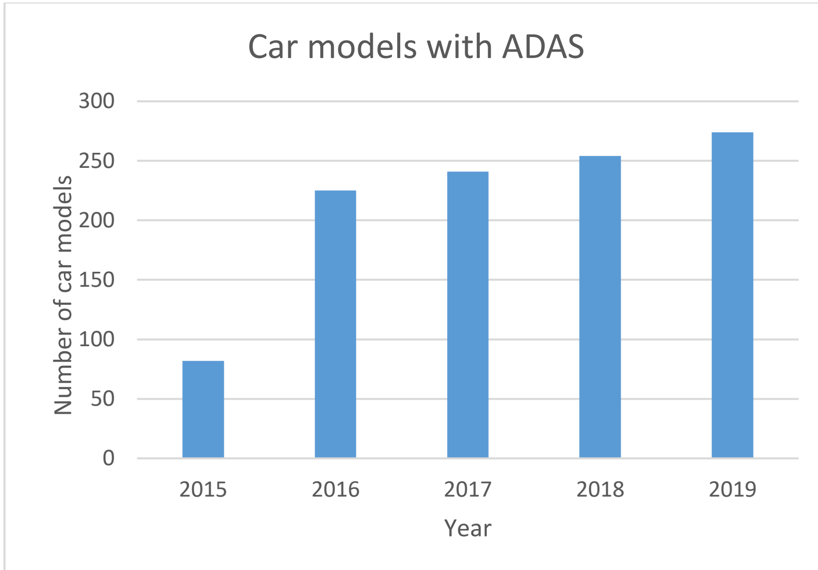

Figure 2: Car Models with ADAS

Researchers at Society of Automotive Engineers (SAE International) introduced levels of self-driving that cars can reach [30]. These levels are described in Figure 3. Almost all of the advanced driver assistance systems that present cars or semi-autonomous cars are equipped with fall under Level 2 driving automation.

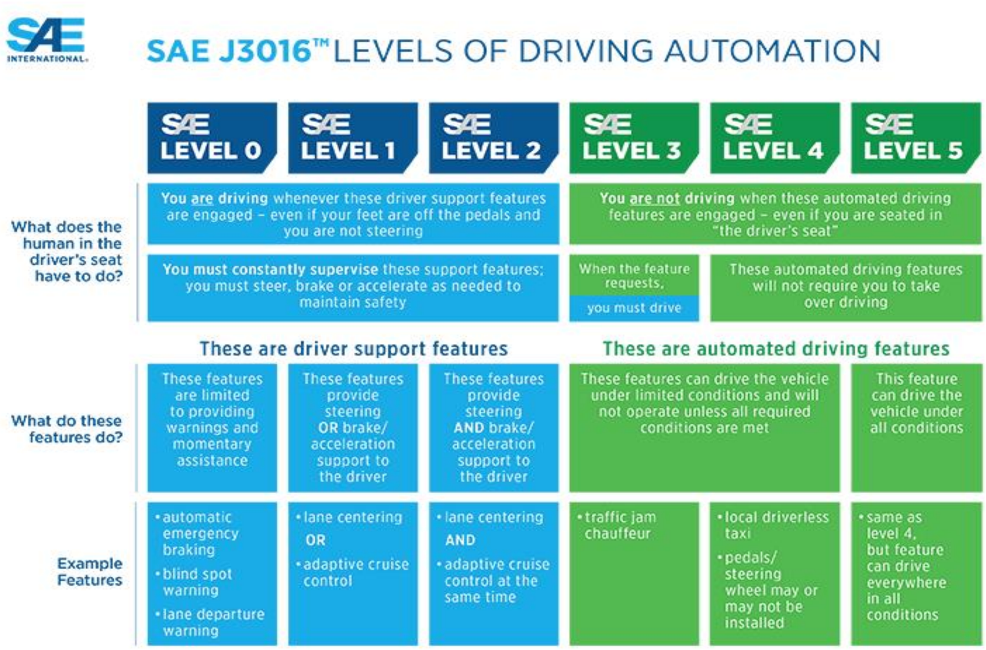

Figure 3: Levels of Driving Automation (adopted from [17])

Given the reputation of autonomous vehicles considering crashes and casualties they have caused, rigorous testing is still underway for these autonomous cars before they are rolled out on the roads again with confidence, which is not a possibility for at least next 5 years.

4.7. Conclusion

There is over hundreds of thousands of lines of code in the car's computer system that accounts for modern semi-autonomous features of the cars and autonomous cars themselves. This opens millions of possibilities to infect the code with bugs and defects and mess with different components of the car simultaneously while the car is being driven on the road. Since self-driving cars leverage wireless technology, Bluetooth, VANETs, V2V communication, Milimeter Wave radar, LiDAR, sensors, and cameras, etc., they are exposed to countless threats, vulnerabilities, and hacking attacks. Any of these technologies can be twisted with some malicious piece of code to gain remote access to the components of a self-driving car making it a potential hazard on the road and demeaning its concept of safe and secure mode of transportation. This paper presented an understanding and study of these technological features behind these autonomous or self-driving cars. This paper also explored, identified, and addressed some popular threats, vulnerabilities, and hacking attacks in self-driving cars. A relationship between these threats, trust and reliability was also established. An analysis of alert systems in self-driving cars was also presented.

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CHAPTER 5. ETHICAL AND LEGAL ISSUES IN HUMAN INTERACTION WITH INTELLIGENT AUTONOMOUS SYSTEMS

5.1. Introduction

Evolution of technology and the advancement of artificial intelligence has led to the creation of autonomous systems allowing them to function with minimal to no human involvement. With the assimilation of governing protocols, manuals and procedures, these autonomous systems have carried out their daily activities in an efficient and effective approach. Amalgamation of machine learning algorithms have furthered their seamless integration into human day to day human activities and lifestyle. Ongoing research and a strong urge to stand out competing technological advancements is improving upon the complexities and robustness of these autonomous systems. However, since it is the human brains behind them, it is bound to err and fail to achieve a behavior, working pattern and decision making sense, that of a human brain. Several academic, industry research studies and technical white papers have documented and published achievements of designing and testing autonomous vehicles and has successfully gained interest of National Highway Traffic Safety Administration (NHTSA) and Department of Transportation (DOT).

NHTSA categorized safety features into five eras as they were introduced into vehicles which depicted a significant improvement in vehicle operability on the roads and a promise towards overall reduction of crashes and accidents. Along with the acknowledgement of six levels of automation levels as deduced by the Society of Automotive Engineers (SAE) and with the interest in an anticipated integration of Autonomous vehicles on U.S roadways by 2035 [8], NHTSA has begun seeking inputs on testing vehicles that are equipped with automated driving systems technologies [12]. The path to this anticipated future has been paved by the extant conscientious literature on the research of autonomous vehicles which holds surplus amounts of information in terms of concepts, studies, theories, hypothesis, testing data and so forth.

Studies have also been reported to work in the direction of incorporating understanding of emotions and decision making capabilities into these autonomous systems, all of which is yet to be trusted to operate autonomously amongst us humans. Another importance aspect is the incorporation of moral and ethical values into these autonomous systems, the concept of which is relative. Lack of standard development and operating procedures makes it even more difficult to integrate these moral and ethical values. Moreover, these autonomous systems are also ensued by the legal issues and policies associated to their operability.

This chapter aims to understand and study the ethical relationship between human and autonomous vehicles (one aspect of autonomous systems) while exploring the avenues of research work and literature in this area. Another goal of this chapter is to identify, study and characterize the policies, ethical and moral values and, legal issues as they relate to autonomous vehicles.

The rest of the chapter is organized as follows. Section 5.2 explores the moral and ethical relationship between human and machine as it relates to autonomous vehicles. Section 5.3 describes policies and legal issues associated with autonomous vehicles.

5.2. Moral and Ethical Relationship between Human and Machine

Existing and current development of autonomous vehicles utilizes non-standard operating procedures which may lead to conflicting decision-making while sharing the road with human drivers. Ethical values and morals correlate with intentionality, a behavior solely possessed by humans. In addition to lack of standard programming procedures, differences in the concepts of intentionality makes it further challenging to incorporate morals into autonomous vehicles. While acknowledging the technical and other related complexities of autonomous vehicles, Borenstien et. al. stated that each designer has ethical obligations that they should consider in terms of creating a safer technology and that “People who design, develop, deploy, promote, or evaluate a computing artifact should not explicitly or implicitly deceive users about the artifact or its foreseeable effects” [2]. They also proposed a value-sensitive design approach that incorporates this thinking and would encourage designers to consider the fact that autonomy, being user’s cherished value, can be sustained during the process of creating their technologies [2].

Amongst the design, development, and successful operation of autonomous vehicles, understanding human machine interaction holds utmost importance which also assimilates morals and ethics. Morals might apply to a situation when conflicting decision-making capabilities of autonomous vehicles are at display. For instance, while merging on a freeway, a human driver might slow down giving way to a merging autonomous vehicle or may speed up not giving way to merging autonomous vehicle. Although, effective ways of programming human morality into software has not been established, there still are several studies that corroborate with each other in deducing methods, techniques, and examples of incorporating morals and ethics into autonomous vehicles. Given the complex nature of real-world scenarios associated with autonomous vehicles, Holstein et. al. segregated and categorized the ethical dilemmas into two categories, viz. technical challenges, and social challenges [4]. Technical challenges focused on safety, security, privacy, trust, transparency, reliability, quality assurance process and responsibility and accountability whereas social challenges covered stakeholders in terms of interest of general public and possible new selling points [4].

Human-machine interaction becomes paramount while human drivers are sharing the roads with autonomous vehicles. However, when two autonomous vehicles are sharing the road, consideration of morals and ethical values and interaction between different autonomous vehicles or two different artificial intelligences becomes important. For instance, while trying to avoid a possible collision with another autonomous vehicle, vehicle A might choose to save the passenger and hit the fire hydrant on the curb, while vehicle B might choose a similar course of action and hit the traffic signal pole. In this situation, if the passengers from both the vehicles get hurt, the moral and ethical values of the vehicles are subject to questioning and criticism. However, if vehicle A does not have any passengers, it might seem ethical for vehicle A to crash itself and engage V2V or V2I communication with vehicle B and allow it to safely pass. Several other such scenarios may exist, all of which would call for a need understand and consider ethical responsibilities of communication between different autonomous vehicles.

In the twentieth century, a renowned biochemist and futurist Isaac Asimov first proposed three robotics laws that are still esteemed and well recognized since they specified that robots must prevent human harm, stipulated obedience to humans and incorporated robotic self-protection. As these laws focused on human-robot interactions, they fell short into addressing ethical inevitability of future interactions and communication between different artificial intelligences [1]. In an attempt to propose humanitarian laws for the protection of rights of robots, with the consideration that they shall not contradict fundamental robotics laws, Ashrafian proposed AIonAI law for robots to support the moral nature of AI to AI interactions [1].

5.3. Policies and Legal Issues with Autonomous Vehicles

Autonomous vehicles were designed with a promise to deliver safe and secure driving operations on roads. However, with the lack of standard design, architecture, and development processes, it has opened loopholes to fall into erroneous situations and opened doors to several legal issues. When human drivers get into accidents or fender benders on the road, they have discussions, rebuttals, and arguments in their defense. Whereas, in the cases of self-driving cars getting into accidents, would it be the owner of the vehicle or the manufacturer of the vehicle facing the legal ramifications, is a greater question. Legal implications apply to these vehicles during the programming and development of these cars as well as while they are operating on the roads. Most of the legal aspects of autonomous vehicles are reliant on vehicle's predictability in arduous situations.

Most countries around the world have been operating autonomous trains and buses for almost a decade now. However, technological developments in the automobile industry and the deployment of autonomous vehicles in the past few years has pressurized the governments to establish policies and regulations to accommodate testing of these vehicles. Nevada (USA) became the first state where the government made regulatory changes to permit on-road testing of autonomous vehicles. Figure 4 illustrates the automated vehicle test sites in US as identified by NHTSA as of March 2019.

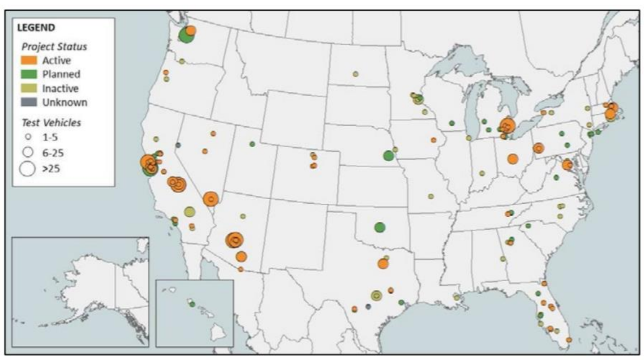

Figure 4: Map of U.S. Automated Vehicle Test Sites (adopted from [8])

Per NHTSA, all automated vehicles and their equipment will be highly regulated by them and that all vehicles will be subject to existing Federal Motor Vehicle Safety Standards (FMVSS). They issued a preliminary statement of policy concerning autonomous vehicles which focused on describing developments in automated driving and explained different levels of automation defined by NHTSA along with providing an overview of automated research program conducted by NHTSA. This statement also provided “recommended principles that States may wish to apply as part of their considerations for driverless vehicle operation, especially with respect to testing and licensing” [9].

Hanna and Kimmel studied and surveyed US government policies and activities that impact the development of automated driving systems while especially emphasizing on cybersecurity, user data privacy, safety regulation, energy and environment, and ethical issues [3]. They credited agencies like US Department of Transportation (USDOT), US Department of Energy (DOE), National Science Foundation (NSF) and National Aeronautics and Space Administration (NASA) that have been funding research that helped create economic opportunities by enabling security, safety assurance, energy efficiency, and data sharing [3].

DOE led the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium in pursuit of understanding system level impacts aimed to deliver new Energy Efficient Mobility Systems (EEMS) data, modeling tools, analysis, and create new knowledge for supporting smarter mobility systems [7]. Another initiative by DOE for developing energy efficient vehicle automation technologies is NEXTCAR (Next-Generation Energy Technologies for Connected and Automated On-Road Vehicles) which claims to reduce energy consumption of future and automated vehicles by 20% by co-optimizing vehicle dynamic controls and powertrain operation with the use of connectivity and automation [5]. The understanding of impacts has also been second by the pursuit of Smart Cities Challenge and University Transportation center programs.

On June 28, 2017, in a joint effort, NHTSA and Federal Trade Commission (FTC) held a workshop to discuss several issues related to data collected by connected and automated vehicles as well as the consumer privacy and security issues posed by these vehicles [6]. These included types of data collected, stored, transmitted and shared by the vehicles with wireless interfaces; potential challenges posed by this data collection and possible benefits; security and privacy practices that the vehicle manufacturer follows; the role that NHTSA, FTC and other government agencies play concerning security and privacy issues related to connected and automated vehicles; and other self-regulatory standards [6]. In July 2017, U.S. Government Accountability Office (GAO) issued a vehicle data privacy report in a wake to review consumer privacy issues that are related to connected vehicles [13].

In September 2017, Senate and the House of Representatives passed SELF DRIVE Act (Safely Ensuring Lives Future Deployment and Research In Vehicle Evolution Act, H.R. 3388) with the purposes of memorializing “the Federal role in ensuring the safety of highly automated vehicles as it relates to design, construction, and performance, by encouraging the testing and deployment of such vehicles” [11]. It expected DOT to require submission of safety certifications for the development of automated driving systems (ADS) or highly automated vehicles (HAVs). It also required the manufactures of HAVs and ADS to provide written cybersecurity policy and privacy plans (including manufacturer’s practices for detecting and responding to unauthorized intrusions, cyberattacks, false or spurious messages or vehicle control commands) before offering these vehicles for sales [11].

In November 2017, American Vision for Safer Transportation Through Advancement of Revolutionary Technologies (AV START) Act was introduced with the purposes of providing enhanced safety oversight (requiring automobile manufacturers to submit safety evaluation report to DOT); reinforcing Federal, State and local roles (ensuring DOT’s responsibility for regulating ADS and HAVs with respect to safety evaluation report); reducing barriers to deployment of vehicles; providing DOT with technical expertise required to set new and updated safety regulations; help DOT modernize existing Federal Motor Vehicle Safety Standards with regards to HAVs; strengthening cybersecurity protections and increase awareness and; improving vehicle safety and data sharing [10].

The existence of these policies and inclusion of several government agencies enforce strict regulations on automobile industries and manufactures towards safe and secure development and deployment of autonomous vehicles.

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CHAPTER 6. TRUST, INTENTION AND ANTI-AUTONOMY MODELLING

6.1. Introduction

Trust in autonomous vehicles is driven by several factors such as the level of automation incorporated in the vehicle (partially autonomous or fully autonomous), its ability to operate safely while sharing the roads with other autonomous vehicles, human drivers, pedestrians, bicyclists, other moving or stationary objects. Other factors include driving through construction zones, weather conditions with limited visibility, the ethical decision making ability of vehicles driving in autonomous driving mode when they encounter situations where other drivers/pedestrians/bicyclists break traffic laws; to name a few. When higher percentage of collisions involving autonomous vehicles surface, it discourages overall intention of people trying to own and adopt autonomous vehicles. It also sparks the notions of anti-autonomy (conduct of autonomous vehicles that goes against the principles of autonomy). In order to expand the knowledge and understanding of the concept of anti-autonomy, learn about its impact on human trust in autonomy along with gaining insights on the potential threats that autonomous vehicles are prone to, extensive research work was performed and published as journal and conference proceeding articles. The contributions made in these published articles inspired, progressed and lead to the quest to search for collision data caused by autonomous vehicles. Despite the fact that collision reports were submitted by the manufacturers licensed to perform testing of their autonomous vehicles in the state of California, they still accounted for significant amount of collisions, injuries and property damage while involving a human-in-the-loop who were frightened even when the vehicle was operating autonomously. The very essence of feeling unsafe and doubtful about the vehicle operation add enough cause for not relying on technology behind the idea of autonomous vehicles.

Several studies have been conducted to understand the preliminary factors responsible for trusting and adopting technologies offered by autonomous vehicles. Trust has been known to be an important determinant of relying on automation and accepting it mediating beliefs of people towards automation and their intentions of taking advantage of it [3]. Choi and Ji utilized trust theory for predicting and examining users' adoption of autonomous vehicles and presented an extension of technology acceptance model. They used 10 constructs in their model viz. trust, perceived ease of use, perceived usefulness, perceived risk, technical competence, system transparency, locus of control, situation management and sensation seeking as prevailing variables and used behavioral intention as dependent variable [3]. The results of their study suggested trust and perceived usefulness as important determinants of intention to use autonomous vehicles while locus of control among driving-related personality traits to be significantly affecting behavioral intention. Also, the fact that trust negatively impacted perceived risk [3]. In their study to explore the use, adoption and appeal of new vehicle technologies and transportation alternatives, Abraham et. al. conducted a survey across users of all ages to assemble information on their satisfaction with current technologies in their vehicles, their inclination on using different levels of automation and transportation alternatives to driving their own cars and methods of learning to use technology in their vehicles [1]. Their survey results concluded that even though older respondents (who could benefit from the technology the most) were willing to use some level of automation, they showed some hesitation in comfort with full autonomy as opposed to younger drivers. Most of the older drivers were also found to have discomfort to surrender control to a system which they believed was less experienced as compared to their lifetime of driving experience or a system they could not fully comprehend [1].

Autonomous vehicles being involved in collisions often questions its autonomous behavior when sharing the roads with human drivers, pedestrians, bicyclists, other objects, and other autonomous vehicles. Even when the analysis of the collision reports pronounces them not guilty, despite the vehicle operating in autonomous mode or conventional mode when human took the control of the vehicle; the fact that the existence of autonomous vehicles - which was supposed to save lives and reduce traffic accidents, itself gets involved in a collision, it does put a dent on overall trust in the vehicle. Collision reports involving autonomous vehicles also brings in the topic of liability of the manufacturer of the vehicle. In their work on liability and regulation of autonomous vehicle technologies, Kalra et. al. evaluated the assignment of responsibility in crashes that involved autonomous vehicle technologies under the existing liability regime [5]. Upon identifying the legal principles that control the crashes which involve autonomous vehicle technologies and examining further development and adoption implications [5], authors concluded the likelihood of autonomous vehicle technologies in reducing liability for drivers but increasing liability for manufacturers since perceived responsibility for crashes move from drivers to the vehicle [4] [5] [7]. To this, they suggested that a standardized operation of these technologies among manufacturers in order for the technologies to function consistently regardless of the vehicle manufacturer, will help in reducing the collisions that stem from consumer confusion [5].

Another potential challenge is to blend the autonomous vehicles into a society with human drivers. There are incidents where human drivers can trick the autonomous vehicle on an intersection into paralyzing the internal system of the vehicle [8] which could lead to gridlocks and congestion on intersections. This unexpected operational behavior of the autonomous vehicle can spark notions of their anti-autonomous capabilities. If autonomous vehicles are often found to behave mysteriously beyond the comprehension of fellow human drivers or their behavior could not be aligned with local governing traffic laws, it raises suspicions towards either a faulty non-standardized design of the autonomous vehicle or the fact that the internal controls of the vehicles had been remotely hacked and compromised. The fact that technology behind the autonomous vehicle comprises of complex lines of code prone to hacking attacks, it opens a myriad of questions on trust and reliability on autonomous vehicles. An autonomous vehicle can be hacked and re-programmed to be self-destructive, not only causing harm and injuries to the driver and passenger but also causing accidents with other drivers around it. This circles back to the concept of who to be held responsible for the wrong actions and behavior of an autonomous vehicle.

Design, development, and manufacturing of autonomous vehicles incorporated with advanced state-of-the-art technologies does not always give user enough confidence to trust and an intention to adopt and potentially own these vehicles. Reason being higher levels of associated risk, safety, and liability issues. Trust and adoption intentionality of the user and trusting the intentionality of the manufacturer’s promise to deliver advanced safe and secure technological features in autonomous vehicles that not only minimize the collisions but also relieve traffic congestions can only be achieved through a thorough in-depth analysis of existing collision data via application of AI, deep learning and machine learning concepts. This chapter presents a data-centric NoTrust ANN model to understand, characterize and analyze collision reports of traffic incidents involving autonomous vehicles with the help of deep learning and machine learning concepts and algorithms. This chapter also aims to utilize the model evaluation and predictions to identify, derive and quantify a relationship between trust, intentionality, anti-autonomy, risk and safety.

The rest of the chapter is organized as follows. Section 6.2 describes the NoTrust ANN model including environment setup, dataset information and augmentation, data labelling, classification and pre-processing, development of sequential ANN model, model training, predictions, and performance. Section 6.3 utilizes the model evaluations and predictions and data analysis to draw a relationship between trust, intentionality, anti-autonomy, risk, and safety.

6.2. NoTrust ANN Model

A NoTrust anti-autonomy artificial neural network (ANN) model was created from autonomous vehicle collision reports obtained from California DMV in PDF format (see Appendix figures B1 through B8 for screen capture of sample PDF reports) between October 2014 and March 2020. This data was converted into tabular data in CSV format (see Appendix figure B9 for screen capture of the CSV data file). Conversion into tabular data in CSV format is important for data labelling, classification, pre-processing, and subsequent model generation. Tabular data from CSV or the structured data was first labelled. Keras was used to define the model and feature columns were used as a bridge to map from the columns in CSV file (see Appendix figure B9 for screen capture of the CSV data file) to features which were used to train the model. The CSV was first uploaded as a dataframe using Pandas. Then after, an input pipeline to batch was built and rows were shuffled using tf.data API which enabled data handling, reading from CSV format, and performing data transformations. The columns in the CSV were then mapped to features which were used to train the model using feature columns. These feature columns were used to create layers that produced dense Tensor to input into the model. A linear sequential model was built by assembling a stack of layers from Keras library using supervised machine learning concepts.

Data labelling and pre-processing created basis for teaching the model for it to be able to predict future instances. Labelled data was stored in a separate feature column in the dataframe which is also a separate column in the same CSV data file (see Appendix figure B9 for screen capture of the CSV data file). When this data was plotted and a single data point on the plot was looked at, it had all the attributes that made a row in that chart which is also referred to as an observation [2]. This new column contained numeric data which stored binaries to represent trust and do not trust values based on the conditions imposed on other feature columns in the CSV data file (see Appendix figure B9 for screen capture of the CSV data file). Classification supervised learning techniques were then applied on this labelled data to work towards building, evaluating, and predicting a linear sequential model as depicted in Figure 5.

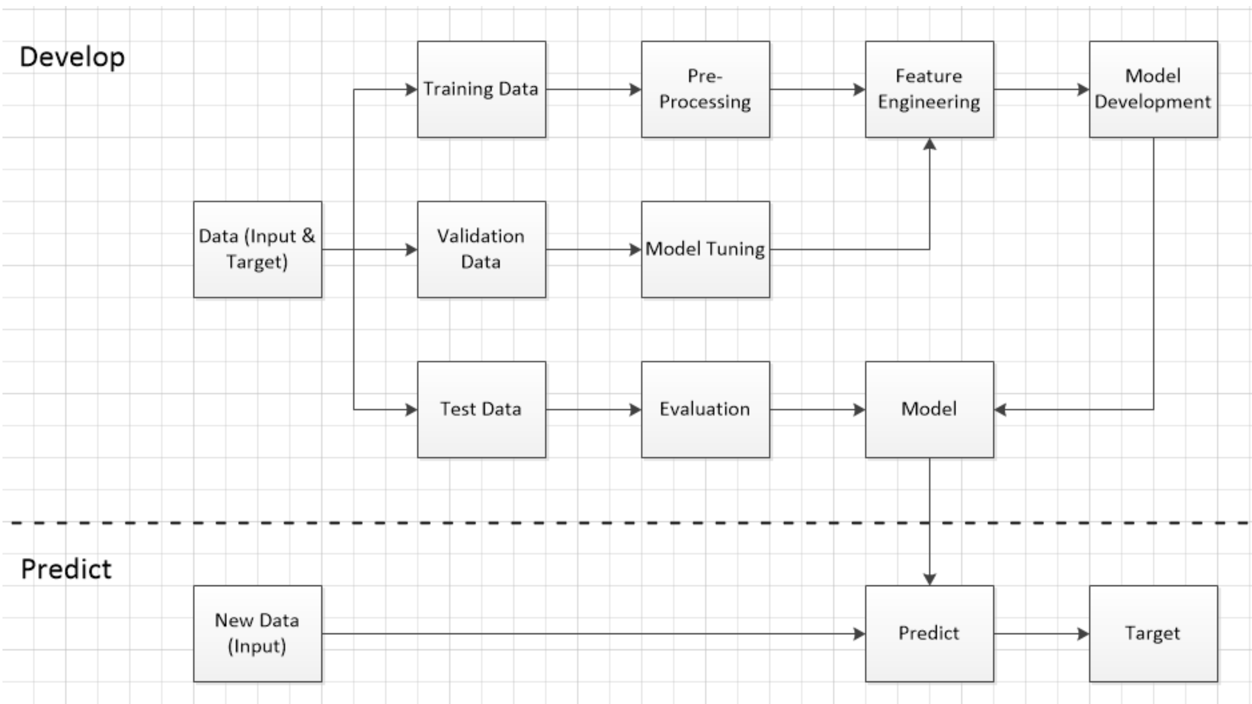

Figure 5: Classified Supervised Learning Techniques for Building a Linear Sequential Model

6.2.1. Environment Setup

TensorFlow with Keras was used to develop the model in Python language since Python is the most widely used language for machine learning algorithms and deep learning problems. And since TensorFlow provides the most stable APIs for Python as compared to other programming languages, it provides seamless integration and implementation. TensorFlow is an open source platform for machine learning which provides tools, libraries and community resources for building and deploying machine learning applications. It was developed by researchers and engineers from Google Brain team within Google's Machine Intelligence Research organization for conducting machine learning and deep neural networks research [13] [14]. TensorFlow works on both CPU and GPU. TensorFlow was installed using pip (python package manager) install using Anaconda command prompt. Python program to build and train the model was written in Jupyter notebook IDE which was also launched using Anaconda prompt. Anaconda is an open source Python data science which manages environment, packages, libraries, and dependencies and helps develop and train machine learning and deep learning models with TensorFlow [11]. Keras was used with Tensorflow backend to develop linear sequential model. Keras is a high-level neural networks API written in Python which provides a deep learning library that allows easy and fast prototyping through user friendliness, extensibility, and modularity; and runs smoothly on CPU and GPU. It also provides standalone modules such as neural layers, cost functions, optimizers, initialization schemes, activation functions and regularization schemes which can be combined to create new models [10]. Keras offers two main types of models – sequential and model with functional API. Sequential model is a linear stack of layers whereas functional API is used for defining complex multi-output models, models with shared layers, or directed acyclic graphs [10]. However, for generating NoTrust model, Keras linear sequential model was used.

Pandas was used for data analysis from the CSV data file since it takes the tabular data from the CSV and creates a dataframe which is a Python object with rows and columns. Pandas is an open source Berkeley Software Development library that provides high-performance data structures and data analysis tools for Python. Anaconda for Python version 3.8.1 was first installed on Windows operating system which provided the environment to use Pandas. Pandas and TensorFlow libraries were imported from which DataFrame, Keras and feature columns were imported. From Keras, layers and sequential model libraries were imported. Matplotlib was imported to plot the graphs. These imported libraries are shown in Figure 6.

```
from __future__ import absolute_import, division, print_function, unicode_literals
import functools

import pathlib
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import tensorflow as tf

np.set_printoptions(precision=4)

from pandas import DataFrame
from tensorflow import feature_column

# import keras layers needed
from tensorflow.keras import layers
from tensorflow.keras.layers import Activation
from tensorflow.keras.layers import Dense

# Import keras Sequential model
from tensorflow.keras.models import Sequential

from sklearn.model_selection import train_test_split
```

Figure 6: Imported Tensorflow Keras Libraries

6.2.2. Dataset Information and Augmentation

Dataset was obtained from public reports of traffic collisions involving autonomous vehicles between October 2014 and March 2020 (which is the latest reported data), that was provided by California Department of Motor Vehicles in PDF format (see Appendix figures B1 through B8 for screen capture of sample PDF reports) [12]. This data was then converted into CSV format in the form of tabular data to be read and processed into Pandas dataframe. A concise list of data attributes is listed in Table 3. All of these data attributes are of Categorical feature type and Object data type. Complete list of these data attributes is listed table A1 in the appendix section of this dissertation.

Table 3: Data Attributes Table

Attribute Type	Attribute Name
PDF File number	PDF file Number
Autonomous vehicle details	Manufacturer Name, Business Name, Vehicle Year, Vehicle Make, Vehicle Model, Vehicle was (stopped in traffic/moving)
Accident Details	Date of Accident, Time of Accident
Involved in Autonomous vehicle accident	Involved in Autonomous Vehicle Accident (Pedestrian/Bicyclist/Other), Number of vehicles involved with Autonomous Vehicle
Autonomous vehicle damage	Vehicle Damage, Damaged Area
Details of other vehicle involved in accident	Vehicle 2 Year, Vehicle 2 Make, Vehicle 2 Model, Vehicle 2 was (stopped in traffic/moving)
Involved in Other vehicle accident	Involved in Vehicle 2 Accident Pedestrian, Involved in Vehicle 2 Accident Bicyclist, Involved in Vehicle 2 Accident Other, Number of vehicles involved with Vehicle 2
Injuries	Injured, Injured Driver, Injured Passenger, Injured Bicyclist
Vehicle driving mode	Vehicle Driving Mode
Weather conditions for both vehicles	Clear, Cloudy, Raining, Snowing, Fog/Visibility, Other, Wind
Lighting conditions for both vehicles	Daylight, Dusk-Dawn, Dark Street Lights, Dark-No Street Lights, Dark-Street Lights Not Functioning
Roadway surface for both vehicles	Dry, Wet, Snowy-Icy, Slippery/Muddy/Oily/etc, Holes-Deep-Rut, Loose Material on Roadway, Obstruction on Roadway, Construction/Repair Zone, Reduced Roadway Width, Flooded, Other, No Unusual Conditions
Preceding Movement of Autonomous Vehicle before collision	Stopped, Proceeding Straight, Ran Off Road, Making Right Turn, Making Left Turn, Making U Turn, Backing, Slowing/Stopping, Passing Other Vehicle, Changing Lanes, Parking Manuever, Entering Traffic, Unsafe Turning, Xing Into Opposing Lane, Parked, Merging, Travelling Wrong Way, Other
Preceding Movement of Other Vehicle before collision	Stopped, Proceeding Straight, Ran Off Road, Making Right Turn, Making Left Turn, Making U Turn, Backing, Slowing/Stopping, Passing Other Vehicle, Changing Lanes, Parking Manuever, Entering Traffic, Unsafe Turning, Xing Into Opposing Lane, Parked, Merging, Travelling Wrong Way, Other
Type of Collision	Head On, Side Swipe, Rear End, Broadside, Hit Object, Overturned, Vehicle/Pedestrian, Other
Other	CVC Sections Violated Cited, Vision Obscurement, Inattention, Stop and Go Traffic, Entering/Leaving Ramp, Previous Collision, Unfamiliar With Road, Defective WEH Equip Cited, Uninvolved Vehicle, Other, None Apparent, Runaway Vehicle

There was a total of 256 collision reports reported by the autonomous vehicle manufacturers to the California DMV (between October 2014 and March 2020) which was converted into CSV format which amounted to 256 rows of data in 140 columns (Figure 7). Since there were only 256 vehicle crash reports, data in the CSV was augmented to yield a model with minimal noise. Data was augmented to 5256 rows based upon the augmentation criteria as described in Table 4.

Table 4: Data Augmentation Criteria

<table>
<tr><th>Column Name</th><th>Augmentation Criteria</th></tr>
<tr><td>PDF_file_Number</td><td>Row index concatenated to the name of the PDF file</td></tr>
<tr><td>Manufacturer_Name</td><td>A string randomly selected from the following existing Manufacturer names – Aimotive Inc., Apple Inc., Aurora Innovation Inc., Cruise LLC, Cruise Automation Inc., Delphi Automotive Systems Inc, Drive.ai Inc., GM Cruise LLC, Lexus, Google Auto LLC, Jingchi Corp, Lyft Inc., Nissan North America INC, Pony.AI Inc., Toyota Research Institute Inc., UATC LLC, Waymo LLC, Zoox Inc.</td></tr>
<tr><td>Business_Name</td><td>Business_Name = Manufacturer_Name</td></tr>
<tr><td>Date_of_Accident</td><td>start_date = datetime.date(2014, 10, 1)
end_date = datetime.date(2020, 3, 31)
time_between_dates = end_date - start_date
days_between_dates = time_between_dates.days
random_number_of_days = random.randrange(days_between_dates)
random_date = start_date + datetime.timedelta(days=random_number_of_days)
Date_of_Accident = random_date.strftime("%m/%d/%Y")</td></tr>
<tr><td>Time_of_Accident</td><td>random_hour = random.randrange(0,23)
random_min = random.randrange(0,59)
Time_of_Accident = str(random_hour) + ':' + str(random_min)</td></tr>
<tr><td>Vehicle_1_Year</td><td>Vehicle1Year = random.randrange(2010,2020)</td></tr>
<tr><td>Vehicle_1_Make</td><td>Vehicle_1_Make was mapped to its respective Manufacturer as follows –
<table>
<tr><td>Manufacturer</td><td>Vehicle 1 Make</td></tr>
<tr><td>Delphi Automotive Systems Inc</td><td>Audi</td></tr>
<tr><td>Cruise LLC or GM Cruise LLC</td><td>Chevrolet</td></tr>
<tr><td>Waymo LLC</td><td>Chrylser</td></tr>
<tr><td>Lyft Inc.</td><td>Ford</td></tr>
<tr><td>Google Auto LLC</td><td>a random string between Google and prototype</td></tr>
<tr><td>Apple Inc. or Lexus or Google Auto LLC or Toyota Research Institute Inc</td><td>Lexus</td></tr>
<tr><td>Aurora Innovation Inc. or Jingchi Corp or Pony.AI Inc.</td><td>Lincoln</td></tr>
<tr><td>Cruise Automation Inc. or Drive.ai Inc. or Nissan North America INC</td><td>Nissan</td></tr>
<tr><td>Aimotive Inc. or Zoox Inc.</td><td>Toyota</td></tr>
<tr><td>UATC LLC</td><td>Volvo</td></tr>
</table></td></tr>
</table>

Table 4: Data Augmentation Criteria (continued)

<table>
<tr><th>Column Name</th><th>Augmentation Criteria</th></tr>
<tr><td>Vehicle_1_Model</td><td>Vehicle_1_Model was mapped to its respective Vehicle_1_Make as follows –
<table>
<tr><th>Vehicle 1 Make</th><th>Vehicle 1 Model</th></tr>
<tr><td>Chevrolet</td><td>Bolt</td></tr>
<tr><td>Ford</td><td>A random string between Fusion and Fusion Hybrid</td></tr>
<tr><td>Toyota</td><td>Highlander</td></tr>
<tr><td>Nissan</td><td>A random string between Leaf and NV200 Taxi</td></tr>
<tr><td>Lexus</td><td>LX 600H L</td></tr>
<tr><td>Lincoln</td><td>MKZ</td></tr>
<tr><td>Chrylser</td><td>Pacifica</td></tr>
<tr><td>Toyota</td><td>Prius</td></tr>
<tr><td>prototype</td><td>Prototype</td></tr>
<tr><td>Lexus</td><td>RX450h</td></tr>
<tr><td>Google</td><td>Self Driving Car</td></tr>
<tr><td>Audi</td><td>SQ5</td></tr>
<tr><td>Volvo</td><td>XC90</td></tr>
</table></td></tr>
<tr><td>Vehicle_1_was</td><td>A random generated string between Moving, Stopped in Traffic and Unknown</td></tr>
<tr><td>Involved_in_Vehicle_1_Accident_Pedestrian</td><td>A random generated string between Yes and No</td></tr>
<tr><td>Involved_in_Vehicle_1_Accident_Bicyclist</td><td>A random generated string between Yes and No</td></tr>
<tr><td>Involved_in_Vehicle_1_Accident_Other</td><td>A random generated string between Yes and No</td></tr>
<tr><td>Number_of_vehicles_involved_with_Vehicle_1</td><td>A random generated string between 1, 2, 3 and Unknown</td></tr>
<tr><td>Vehicle_Damage</td><td>A random generated string between Major, Minor, Moderate, None and Unknown</td></tr>
<tr><td>Damaged_Area</td><td>if Vehicle_Damage is 'None':
Damaged_Area = 'None'
else:
Damaged_Area = random.choice(['Front', 'Front and Left Side', 'Left Front', 'Left Rear', 'Left Side', 'Rear', 'Right Front', 'Right Rear', 'Right Side', 'Unknown'])</td></tr>
<tr><td>Vehicle_2_Year</td><td>if Number_of_vehicles_involved_with_Vehicle_1 is '1':
Vehicle_2_Year = 'Not Applicable'
else:
Vehicle_2_Year = random.choice (['1984', '1993', '1994', '1995', '1996', '1997', '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005', '2006', '2007', '2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015', '2016', '2017', '2018', '2019', 'Unknown'])</td></tr>
<tr><td>Vehicle_2_Make</td><td>if Number_of_vehicles_involved_with_Vehicle_1 is '1':
Vehicle_2_Make = 'Not Applicable'
else:
Vehicle_2_Make = random.choice (['All Weather Architectural Aluminum Frieghtliner/Hino Truck','Audi','Bicycle','BMW','Buick', 'Bus','Cadillac','Chevrolet','Chrysler','Dodge','Ford','Genuine', 'Genza 2.0f electric scooter', 'Gillig Low Floor Bus','Honda','Hyundai','Infinity','Isuzu','Jeep', 'Kawasaki', 'Kia', 'Lexus', 'Mazda', 'Mercedes', 'Mitsubishi', 'Newflyer', 'Nissan', 'NPR', 'Pickup Truck', 'Porsche', 'Scion', 'Subaru', 'Tesla', 'Toyota', 'Unknown', 'Vespa', 'Volkswagen', 'Volvo', 'Yamaha'])</td></tr>
</table>

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria
Vehicle_2_Model	Vehicle_2_Model was mapped to its respective Vehicle_1_Make as follows –

Vehicle 2 Make	*Vehicle 2 Model*
All Weather Architectural Aluminum Frieghtliner/Hino Truck	Unknown
Audi	A random string between A4, A6, Q4, Q5 and Unknown
Bicycle	Unknown
BMW	A random string between 3 Series, 325i, 328 IX, 328ci, 328i, 528i, 535i, 633 Csi, Unknown and X5M
Buick	LaSabre
Bus	Unknown
Cadillac	A random string between Seville and Unknown
Chevrolet	A random string between Bolt, Cobalt, Equinox, Silverado, SuburbanK1500, Traverse and Unknown
Chrysler	Town & Country
Dodge	A random string between Charger, Journey and Sprinter
Ford	A random string between C-Max, Econoline E-150, Escape, Expedition, Explorer, Explorer XLT, F-250, F250 Super Duty, Fiesta, Fusion, Ranger, Taurus, Transit, Transit 250 Low Roof and Unknown
Genuine	Scooter
Genuine 2.0f electric scooter	Unknown
Gillig Low Floor Bus	Unknown
Honda	A random string between Accord, CB300F, Civic, Civic EX, Civic LX, Clarity, CRV, Cr-V Ex, Odyssey, PCX 150, Rebel, Ridgeline, S90 and Unknown
Hyundai	A random string between Accent, Elantra, Ioniq and Unknown
Infinity	M35
Isuzu	A random string between NPR and Unknown
Jeep	A random string between Cherokee, Wrangler and Unknown
Kawasaki	Ninja 300
Kia	A random string between Sportage and Soul Sport
Lexus	A random string between ES, IS250, IS350, LS400, RX350 and Unknown
Mazda	A random string between 2, 3, 5, 3 SW S, B2300, CX-5 Grand Touring 4D UTV, Protégé 5 and Unknown
Mercedes	A random string between Benz, Benz C300, Benz E Class 4D 2WD 350, ML350, Sprinter and Sprinter 25004X2
Mitsubishi	Unknown
Newflyer	Lowfloor Articulated Bus, Series 2300
Nissan	A random string between Altima, Altima XL, Armada, Frontier, Leaf, NV200S, Sentra and Versa
None	None
Not Applicable	Not Applicable
NPR, Pickup Truck, Vespa	Unknown
Porsche	Panamera
Scion	xA
Subaru	A random string between Forester, Impreza and Outback
Tesla	A random string between Model 3 and Model S
Toyota	A random string between 86, 4Runner, Avalon, Camry, Camry SE, Celica, Corolla, Highlander, Prius, RAV4, RAV4 EV, Sienna, Tacoma, Yaris and Unknown
Unknown	A random choice between Minivan and Unknown
Volkswagen	Jetta, Passat, Tiguan and Unknown
Volvo	V40
Yamaha	YZF-R3

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria
Vehicle_2_was	A random generated string between Moving, Moving and Stopped in Traffic, Not Applicable, Stopped in Traffic and Unknown

Involved_in_Vehicle_2_Accident_Pedestrian	if Number_of_vehicles_involved_with_Vehicle_1 is '1':
	Involved_in_Vehicle_2_Accident_Pedestrian = 'Not Applicable'
	else:
	Involved_in_Vehicle_2_Accident_Pedestrian = Involved_in_Vehicle_1_Accident_Pedestrian

Involved_in_Vehicle_2_Accident_Bicyclist	if Number_of_vehicles_involved_with_Vehicle_1 is '1':
	Involved_in_Vehicle_2_Accident_Bicyclist = 'Not Applicable'
	else:
	Involved_in_Vehicle_2_Accident_Bicyclist = Involved_in_Vehicle_1_Accident_Bicyclist

Involved_in_Vehicle_2_Accident_Other	if Number_of_vehicles_involved_with_Vehicle_1 is '1':
	Involved_in_Vehicle_2_Accident_Other = 'Not Applicable'
	else:
	Involved_in_Vehicle_2_Accident_Other = Involved_in_Vehicle_1_Accident_Other

Number_of_vehicles_involved_with_Vehicle_2	if Number_of_vehicles_involved_with_Vehicle_1 is '1':
	Number_of_vehicles_involved_with_Vehicle_2 = random.choice (['0', '1', 'Not Applicable', 'Unknown'])
	elif Number_of_vehicles_involved_with_Vehicle_1 is '2':
	Number_of_vehicles_involved_with_Vehicle_2 = random.choice (['2', 'Unknown'])
	elif Number_of_vehicles_involved_with_Vehicle_1 is '3':
	Number_of_vehicles_involved_with_Vehicle_2 = '3'
	else:
	Number_of_vehicles_involved_with_Vehicle_2 = random.choice (['1', '2', 'Not Applicable', 'Unknown'])

Injured	A random generated string between Yes, No and Unknown. if Involved_in_Vehicle_1_Accident_Bicyclist is 'Yes': Injured = 'Yes'

Injured_Driver	if Injured is 'Unknown':
	Injured_Driver = 'Unknown'
	elif Involved_in_Vehicle_1_Accident_Bicyclist is 'Yes':
	Injured_Driver = random.choice (['Yes', 'No'])
	elif Injured is 'Yes':
	Injured_Driver = random.choice (['Yes', 'No'])

Injured_Passenger	if Injured is 'Unknown':
	Injured_Passenger = 'Unknown'
	elif Involved_in_Vehicle_1_Accident_Bicyclist is 'Yes':
	Injured_Passenger = random.choice (['Yes', 'No'])
	elif Injured is 'Yes':
	Injured_Passenger = random.choice (['Yes', 'No'])

Injured_Bicyclist	if Injured is 'Unknown':
	Injured_Bicyclist = 'Unknown'
	elif Involved_in_Vehicle_1_Accident_Bicyclist is 'Yes':
	Injured_Bicyclist = 'Yes'
	elif Injured is 'Yes':
	Injured_Bicyclist = Involved_in_Vehicle_1_Accident_Bicyclist

Vehicle_Driving_Mode	A random generated string between Autonomous Mode and Conventional Mode

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_1_Weather_Clear	Vehicle_1_Weather_Clear = random.choice(['Yes', 'No'])
	if Vehicle_1_Weather_Cloudy is 'Yes':
	    Vehicle_1_Weather_Clear = 'No'
	elif Vehicle_1_Weather_Raining is 'Yes':
	    Vehicle_1_Weather_Clear = 'No'
	
	if Vehicle_Damage is 'Unknown':
	    Vehicle_1_Weather_Clear = 'Unknown'

Vehicle_2_Weather_Clear	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Weather_Clear = Vehicle_1_Weather_Clear
	elif Vehicle_Damage is 'Unknown':
	    Vehicle_2_Weather_Clear = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Weather_Clear = 'Not Applicable'

Vehicle_1_Weather_Cloudy	Vehicle_1_Weather_Cloudy = random.choice(['Yes', 'No'])
	if Vehicle_1_Weather_Clear is 'Yes':
	    Vehicle_1_Weather_Cloudy = 'No'
	elif Vehicle_1_Weather_Raining is 'Yes':
	    Vehicle_1_Weather_Cloudy = 'No'
	
	if Vehicle_Damage is 'Unknown':
	    Vehicle_1_Weather_Cloudy = 'Unknown'

Vehicle_2_Weather_Cloudy	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Weather_Cloudy = Vehicle_1_Weather_Cloudy
	elif Vehicle_Damage is 'Unknown':
	    Vehicle_2_Weather_Cloudy = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Weather_Cloudy = 'Not Applicable'

Vehicle_1_Weather_Raining	Vehicle_1_Weather_Raining = random.choice (['Yes', 'No'])
	if Vehicle_1_Weather_Clear is 'Yes':
	    Vehicle_1_Weather_Raining = 'No'
	elif Vehicle_1_Weather_Cloudy is 'Yes':
	    Vehicle_1_Weather_Raining = 'No'
	
	if Vehicle_Damage is 'Unknown':
	    Vehicle_1_Weather_Raining = 'Unknown'

Vehicle_2_Weather_Raining	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Weather_Raining = Vehicle_1_Weather_Raining
	elif Vehicle_Damage is 'Unknown':
	    Vehicle_2_Weather_Raining = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Weather_Raining = 'Not Applicable'

Vehicle_1_Weather_Snowing	Vehicle_1_Weather_Snowing = 'No' if Vehicle_Damage is 'Unknown': Vehicle_1_Weather_Snowing = 'Unknown'

Vehicle_2_Weather_Snowing	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Weather_Snowing = Vehicle_1_Weather_Snowing
	elif Vehicle_Damage is 'Unknown':
	    Vehicle_2_Weather_Snowing = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Weather_Snowing = 'Not Applicable'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_1_Weather_Fog/Visibility	if Vehicle_1_Weather_Clear is 'Yes':
	Vehicle_1_Weather_Fog/Visibility = 'No'
	elif Vehicle_1_Weather_Cloudy is 'Yes':
	Vehicle_1_Weather_Fog/Visibility = 'No'
	elif Vehicle_1_Weather_Raining is 'Yes':
	Vehicle_1_Weather_Fog/Visibility = 'No'
	else:
	Vehicle_1_Weather_Fog/Visibility = 'Yes'
	
	if Vehicle_Damage is 'Unknown':
	Vehicle_1_Weather_Fog/Visibility = 'Unknown'

Vehicle_2_Weather_Fog/Visibility	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Weather_Fog/Visibility = Vehicle_1_Weather_Fog/Visibility
	elif Vehicle_Damage is 'Unknown':
	Vehicle_2_Weather_Fog/Visibility = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Weather_Fog/Visibility = 'Not Applicable'

Vehicle_1_Weather_Other	Vehicle_1_Weather_Other = 'No' if Vehicle_Damage is 'Unknown': Vehicle_1_Weather_Other = 'Unknown'

Vehicle_2_Weather_Other	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Weather_Other = Vehicle_1_Weather_Other
	elif Vehicle_Damage is 'Unknown':
	Vehicle_2_Weather_Other = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Weather_Other = 'Not Applicable'

Vehicle_1_Weather_Wind	Vehicle_1_Weather_Wind = 'No' elif Vehicle_Damage is 'Unknown': Vehicle_1_Weather_Wind = 'Unknown'

Vehicle_2_Weather_Wind	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Weather_Wind = Vehicle_1_Weather_Wind
	elif Vehicle_Damage is 'Unknown':
	Vehicle_2_Weather_Wind = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Weather_Wind = 'Not Applicable'

Vehicle_1_Lighting_Daylight	Vehicle_1_Lighting_Daylight = random.choice (['Yes', 'No'])
	if Vehicle_1_Lighting_Dusk-Dawn is 'Yes':
	Vehicle_1_Lighting_Daylight = 'No'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Lighting_Daylight = 'Unknown'

Vehicle_2_Lighting_Daylight	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Lighting_Daylight = Vehicle_1_Lighting_Daylight
	elif Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Lighting_Daylight = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Lighting_Daylight = 'Not Applicable'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_1_Lighting_Dusk-Dawn	Vehicle_1_Lighting_Dusk-Dawn = random.choice (['Yes', 'No'])
	
	if Vehicle_1_Lighting_Daylight is 'Yes':
	    Vehicle_1_Lighting_Dusk-Dawn = 'No'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_1_Lighting_Dusk-Dawn = 'Unknown'

Vehicle_2_Lighting_Dusk-Dawn	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Lighting_Dusk-Dawn = Vehicle_1_Lighting_Dusk-Dawn
	elif Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Lighting_Dusk_Dawn = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Lighting_Dusk-Dawn = 'Not Applicable'

Vehicle_1_Lighting_Dark-Street-Lights	if Vehicle_1_Lighting_Daylight is 'Yes':
	    Vehicle_1_Lighting_Dark-Street-Lights = 'No'
	elif Vehicle_1_Lighting_Dusk-Dawn is 'Yes':
	    Vehicle_1_Lighting_Dark-Street-Lights = 'No'
	else:
	    Vehicle_1_Lighting_Dark-Street-Lights = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_1_Lighting_Dark-Street-Lights = 'Unknown'

Vehicle_2_Lighting_Dark-Street-Lights	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Lighting_Dark-Street-Lights = Vehicle_1_Lighting_Dark-Street-Lights
	elif Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Lighting_Dark-Street-Lights = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Lighting_Dark-Street-Lights = 'Not Applicable'

Vehicle_1_Lighting_Dark-No-Street-Lights	Vehicle_1_Lighting_Dark-No-Street-Lights = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Lighting_Dark-No-Street-Lights = 'Unknown'

Vehicle_2_Lighting_Dark-No-Street-Lights	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Lighting_Dark-No-Street-Lights = Vehicle_1_Lighting_Dark-No-Street-Lights
	elif Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Lighting_Dark-No-Street-Lights = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Lighting_Dark-No-Street-Lights = 'Not Applicable'

Vehicle_1_Lighting_Dark-Street-Lights-Not-Functioning	Vehicle_1_Lighting_Dark-Street-Lights-Not-Functioning = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Lighting-Dark-Street-Lights-Not-Functioning = 'Unknown'

Vehicle_2_Lighting_Dark-Street-Lights-Not-Functioning	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Lighting_Dark-Street-Lights-Not-Functioning = Vehicle_1_Lighting_Dark-Street-Lights-Not-Functioning
	elif Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Lighting_Dark-Street-Lights-Not-Functioning = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Lighting_Dark-Street-Lights-Not-Functioning = 'Not Applicable'

Vehicle_1_Roadway_Surface-Dry	Vehicle_1_Roadway_Surface-Dry = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Roadway_Surface-Dry = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Roadway_Surface-Dry	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Roadway_Surface-Dry = Vehicle_1_Roadway_Surface-Dry
	elif Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Roadway_Surface-Dry = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Roadway_Surface-Dry = 'Not Applicable'

Vehicle_1_Roadway_Surface-Wet	if Vehicle_1_Roadway_Surface-Dry is 'Yes':
	Vehicle_1_Roadway_Surface-Wet = 'No'
	else:
	Vehicle_1_Roadway_Surface-Wet = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Roadway_Surface-Wet = 'Unknown'

Vehicle_2_Roadway_Surface-Wet	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Roadway_Surface-Wet = Vehicle_1_Roadway_Surface-Wet
	elif Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Roadway_Surface-Wet = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Roadway_Surface-Wet = 'Not Applicable'

Vehicle_1_Roadway_Surface-Snowy-Icy	Vehicle_1_Roadway_Surface_Snowy-Icy = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Roadway_Surface_Snowy-Icy = 'Unknown'

Vehicle_2_Roadway_Surface-Snowy-Icy	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Roadway_Surface_Snowy-Icy =
	Vehicle_1_Roadway_Surface_Snowy-Icy
	elif Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Roadway_Surface_Snowy-Icy = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Roadway_Surface_Snowy-Icy = 'Not Applicable'

Vehicle_1_Roadway_Surface-Slippery-Muddy-Oily-etc	Vehicle_1_Roadway_Surface-Slippery-Muddy-Oily-etc = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Roadway_Surface-Slippery-Muddy-Oily-etc = 'Unknown'

Vehicle_2_Roadway_Surface-Slippery-Muddy-Oily-etc	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Roadway_Surface-Slippery-Muddy-Oily-etc =
	Vehicle_1_Roadway_Surface-Slippery-Muddy-Oily-etc
	elif Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Roadway_Surface-Slippery-Muddy-Oily-etc = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Roadway_Surface-Slippery-Muddy-Oily-etc = 'Not Applicable'

Vehicle_1_Roadway_Conditions-Holes-Deep-Rut	Vehicle_1_Roadway_Conditions-Holes-Deep-Rut = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Roadway_Conditions-Holes-Deep-Rut = 'Unknown'

Vehicle_2_Roadway_Conditions-Holes-Deep-Rut	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Roadway_Conditions-Holes-Deep-Rut =
	Vehicle_1_Roadway_Conditions-Holes-Deep-Rut
	elif Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Roadway_Conditions_Holes-Deep-Rut = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Roadway_Conditions-Holes-Deep-Rut = 'Not Applicable'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria
Vehicle_1_Roadway_Conditions-Loose-Material-on-Roadway	Vehicle_1_Roadway_Conditions-Loose-Material-on-Roadway = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Roadway_Conditions-Loose-Material-on-Roadway = 'Unknown'

Vehicle_2_Roadway_Conditions-Loose-Material-on-Roadway	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Roadway_Conditions-Loose-Material-on-Roadway = Vehicle_1_Roadway_Conditions-Loose-Material-on-Roadway
	elif Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Roadway_Conditions-Loose-Material-on-Roadway = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Roadway_Conditions-Loose-Material-on-Roadway = 'Not Applicable'

Vehicle_1_Roadway_Conditions-Obstruction-on-Roadway	Vehicle_1_Roadway_Conditions-Obstruction-on-Roadway = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Roadway_Conditions-Obstruction-on-Roadway = 'Unknown'

Vehicle_2_Roadway_Conditions-Obstruction-on-Roadway	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Roadway_Conditions-Obstruction-on-Roadway = Vehicle_1_Roadway_Conditions-Obstruction-on-Roadway
	elif Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Roadway_Conditions-Obstruction-on-Roadway = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Roadway_Conditions-Obstruction-on-Roadway = 'Not Applicable'

Vehicle_1_Roadway_Conditions-Construction-Repair-Zone	Vehicle_1_Roadway_Conditions-Construction-Repair-Zone = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Roadway_Conditions-Construction-Repair-Zone = 'Unknown'

Vehicle_2_Roadway_Conditions-Construction-Repair-Zone	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Roadway_Conditions-Construction-Repair-Zone = Vehicle_1_Roadway_Conditions-Construction-Repair-Zone
	elif Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Roadway_Conditions-Construction-Repair-Zone = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Roadway_Conditions-Construction-Repair-Zone = 'Not Applicable'

Vehicle_1_Roadway_Conditions-Reduced-Roadway-Width	if Vehicle_1_Roadway_Conditions-Construction-Repair-Zone is 'Yes':
	Vehicle_1_Roadway_Conditions-Reduced-Roadway-Width = 'No'
	else:
	Vehicle_1_Roadway_Conditions-Reduced-Roadway-Width = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Roadway_Conditions-Reduced-Roadway-Width = 'Unknown'

Vehicle_2_Roadway_Conditions-Reduced-Roadway-Width	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	Vehicle_2_Roadway_Conditions-Reduced-Roadway-Width = Vehicle_1_Roadway_Conditions-Reduced-Roadway-Width
	elif Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Roadway_Conditions-Reduced-Roadway-Width = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	Vehicle_2_Roadway_Conditions-Reduced-Roadway-Width = 'Not Applicable'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria
Vehicle_1_Roadway_Conditions-Flooded	Vehicle_1_Roadway_Conditions-Flooded = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Roadway_Conditions-Flooded = 'Unknown'

Vehicle_2_Roadway_Conditions-Flooded	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Roadway_Conditions-Flooded = Vehicle_1_Roadway_Conditions-Flooded
	elif Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Roadway_Conditions-Flooded = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Roadway_Conditions-Flooded = 'Not Applicable'

Vehicle_1_Roadway_Conditions-Other	Vehicle_1_Roadway_Conditions-Other = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Roadway_Conditions-Other = 'Unknown'

Vehicle_2_Roadway_Conditions-Other	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Roadway_Conditions-Other = Vehicle_1_Roadway_Conditions-Other
	elif Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Roadway_Conditions-Other = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Roadway_Conditions-Other = 'Not Applicable'

Vehicle_1_Roadway_Conditions-No-Unusual-Conditions	Vehicle_1_Roadway_Conditions-No-Unusual-Conditions = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Roadway_Conditions-No-Unusual-Conditions = 'Unknown'

Vehicle_2_Roadway_Conditions-No-Unusual-Conditions	if Number_of_vehicles_involved_with_Vehicle_1 in ('1', '2', '3'):
	    Vehicle_2_Roadway_Conditions-No-Unusual-Conditions = Vehicle_2_Roadway_Conditions-No-Unusual-Conditions
	elif Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Roadway_Conditions-No-Unusual-Conditions = 'Unknown'
	elif Number_of_vehicles_involved_with_Vehicle_2 is 'Not Applicable':
	    Vehicle_2_Roadway_Conditions-No-Unusual-Conditions = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Stopped	Vehicle_1_Movement_Preceding_Collision-Stopped = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_1_Movement_Preceding_Collision-Backing', 'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_1_Movement_Preceding_Collision-Parked', 'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Stopped':
	    Vehicle_1_Movement_Preceding_Collision-Stopped= 'Yes'
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_1_Movement_Preceding_Collision-Stopped = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

<table>
<tr><th>Column Name</th><th>Augmentation Criteria</th></tr>
<tr><td>Vehicle_2_Movement_Preceding_Collision-Stopped</td><td>Vehicle_2_Movement_Preceding_Collision-Stopped = 'No'

randommovement2 = random.choice
(['Vehicle_2_Movement_Preceding_Collision_Stopped',
'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight',
'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road',
'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn',
'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn',
'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn',
'Vehicle_2_Movement_Preceding_Collision-Backing',
'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping',
'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle',
'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes',
'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever',
'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic',
'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning',
'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane',
'Vehicle_2_Movement_Preceding_Collision-Parked',
'Vehicle_2_Movement_Preceding_Collision-Merging',
'Vehicle_2_Movement_Preceding_Collision-Other'])

if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision_Stopped':
    Vehicle_2_Movement_Preceding_Collision_Stopped = 'Yes'

if Vehicle_1_Weather_Clear is 'Unknown':
    Vehicle_2_Movement_Preceding_Collision-Stopped = 'Unknown'
elif Vehicle_2_Weather_Clear is 'Not Applicable':
    Vehicle_2_Movement_Preceding_Collision-Stopped = 'Not Applicable'</td></tr>
<tr><td>Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight</td><td>Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight = 'No'

randommovement1 = random.choice
(['Vehicle_1_Movement_Preceding_Collision-Stopped',
'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight',
'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road',
'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn',
'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn',
'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn',
'Vehicle_1_Movement_Preceding_Collision-Backing',
'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping',
'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle',
'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes',
'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever',
'Vehicle_1_Movement_Preceding_Collision-Parked',
'Vehicle_1_Movement_Preceding_Collision-Merging'])

if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight':
    Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight = 'Yes'

if Vehicle_1_Weather_Clear is 'Unknown':
    Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight = 'Unknown'

if Vehicle_2_Weather_Clear is 'Not Applicable':
    Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight = 'Not Applicable'</td></tr>
</table>

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_ Preceding_Collision- Proceeding-Straight	Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight':
	Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight = 'Not Applicable'

Vehicle_1_Movement_ Preceding_Collision- Ran-Off-Road	Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_1_Movement_Preceding_Collision-Backing', 'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_1_Movement_Preceding_Collision-Parked', 'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road':
	Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_ Preceding_Collision-Ran-Off-Road	Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road':
	    Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road = 'Yes'
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road = 'Not Applicable'

Vehicle_1_Movement_ Preceding_Collision-Making-Right-Turn	Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_1_Movement_Preceding_Collision-Backing', 'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_1_Movement_Preceding_Collision-Parked', 'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn':
	    Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn	Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn':
	Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn	Vehicle_1_Movement_Preceding_Collision_Making_Left_Turn = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_1_Movement_Preceding_Collision-Backing', 'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_1_Movement_Preceding_Collision-Parked', 'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn':
	Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn	Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn':
	Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Making-U-Turn	Vehicle_1_Movement_Preceding_Collision-Making-U-Turn = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_1_Movement_Preceding_Collision-Backing', 'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_1_Movement_Preceding_Collision-Parked', 'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn':
	Vehicle_1_Movement_Preceding_Collision-Making-U-Turn = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Movement_Preceding_Collision-Making-U-Turn = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Making-U-Turn	Vehicle_2_Movement_Preceding_Collision-Making-U-Turn = 'No'
	
	randommovement2 = random.choice
	(['Vehicle_2_Movement_Preceding_Collision_Stopped',
	'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight',
	'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road',
	'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn',
	'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn',
	'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn',
	'Vehicle_2_Movement_Preceding_Collision-Backing',
	'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping',
	'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle',
	'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes',
	'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever',
	'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic',
	'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning',
	'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane',
	'Vehicle_2_Movement_Preceding_Collision-Parked',
	'Vehicle_2_Movement_Preceding_Collision-Merging',
	'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn':
	    Vehicle_2_Movement_Preceding_Collision-Making-U-Turn = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Movement_Preceding_Collision-Making-U-Turn = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Movement_Preceding_Collision-Making-U-Turn = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Backing	Vehicle_1_Movement_Preceding_Collision-Backing = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight',
	'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road',
	'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn',
	'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn',
	'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn',
	'Vehicle_1_Movement_Preceding_Collision-Backing',
	'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping',
	'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle',
	'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes',
	'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever',
	'Vehicle_1_Movement_Preceding_Collision-Parked',
	'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Backing':
	    Vehicle_1_Movement_Preceding_Collision-Backing = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_1_Movement_Preceding_Collision-Backing = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_ Preceding_Collision- Backing	Vehicle_2_Movement_Preceding_Collision-Backing = 'No'
	
	randommovement2 = random.choice
	(['Vehicle_2_Movement_Preceding_Collision_Stopped',
	'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight',
	'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road',
	'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn',
	'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn',
	'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn',
	'Vehicle_2_Movement_Preceding_Collision-Backing',
	'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping',
	'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle',
	'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes',
	'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever',
	'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic',
	'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning',
	'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane',
	'Vehicle_2_Movement_Preceding_Collision-Parked',
	'Vehicle_2_Movement_Preceding_Collision-Merging',
	'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Backing':
	    Vehicle_2_Movement_Preceding_Collision-Backing = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Movement_Preceding_Collision-Backing = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Movement_Preceding_Collision-Backing = 'Not Applicable'

Vehicle_1_Movement_ Preceding_Collision- Slowing/Stopping	Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight',
	'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road',
	'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn',
	'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn',
	'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn',
	'Vehicle_1_Movement_Preceding_Collision-Backing',
	'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping',
	'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle',
	'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes',
	'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever',
	'Vehicle_1_Movement_Preceding_Collision-Parked',
	'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping':
	    Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping	Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping':
	    Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Movement_Preceding_Collision_Slowing/Stopping = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle	Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_1_Movement_Preceding_Collision-Backing', 'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_1_Movement_Preceding_Collision-Parked', 'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle':
	    Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle	Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle':
	Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Changing-Lanes	Vehicle_1_Movement_Preceding_Collision-Changing-Lanes = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_1_Movement_Preceding_Collision-Backing', 'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_1_Movement_Preceding_Collision-Parked', 'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes':
	Vehicle_1_Movement_Preceding_Collision-Changing-Lanes = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Movement_Preceding_Collision-Changing-Lanes = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Changing-Lanes	Vehicle_2_Movement_Preceding_Collision-Changing-Lanes = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes':
	Vehicle_2_Movement_Preceding_Collision-Changing-Lanes = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Changing-Lanes = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Changing-Lanes = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Parking-Manuever	Vehicle_1_Movement_Preceding_Collision-Parking-Manuever = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_1_Movement_Preceding_Collision-Backing', 'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_1_Movement_Preceding_Collision-Parked', 'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever':
	Vehicle_1_Movement_Preceding_Collision-Parking-Manuever = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Movement_Preceding_Collision-Parking-Manuever = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Parking-Manuever	Vehicle_2_Movement_Preceding_Collision-Parking-Manuever = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever':
	Vehicle_2_Movement_Preceding_Collision-Parking-Manuever = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Parking-Manuever = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Parking-Manuever = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Entering-Traffic	Vehicle_1_Movement_Preceding_Collision-Entering-Traffic = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Movement_Preceding_Collision-Entering-Traffic = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Entering-Traffic	Vehicle_2_Movement_Preceding_Collision-Entering-Traffic = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic':
	Vehicle_2_Movement_Preceding_Collision-Entering-Traffic = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Entering-Traffic = 'Unknown'
	if Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Entering-Traffic = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Other-Unsafe-Turning	Vehicle_1_Movement_Preceding_Collision-Other-Unsafe-Turning = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Movement_Preceding_Collision-Other-Unsafe-Turning = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning	Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning':
	Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Xing-Into-Opposing-Lane	Vehicle_1_Movement_Preceding_Collision-Xing-Into-Opposing-Lane = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Movement_Preceding_Collision-Xing-Into-Opposing-Lane = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane	Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane':
	Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Parked	Vehicle_1_Movement_Preceding_Collision-Parked = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_1_Movement_Preceding_Collision-Backing', 'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_1_Movement_Preceding_Collision-Parked', 'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Parked':
	Vehicle_1_Movement_Preceding_Collision-Parked = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Movement_Preceding_Collision-Parked = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_ Preceding_Collision-Parked	Vehicle_2_Movement_Preceding_Collision-Parked = 'No'
	
	randommovement2 = random.choice
	(['Vehicle_2_Movement_Preceding_Collision_Stopped',
	'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight',
	'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road',
	'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn',
	'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn',
	'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn',
	'Vehicle_2_Movement_Preceding_Collision-Backing',
	'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping',
	'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle',
	'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes',
	'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever',
	'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic',
	'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning',
	'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane',
	'Vehicle_2_Movement_Preceding_Collision-Parked',
	'Vehicle_2_Movement_Preceding_Collision-Merging',
	'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Parked':
	    Vehicle_2_Movement_Preceding_Collision-Parked = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Movement_Preceding_Collision-Parked = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Movement_Preceding_Collision-Parked = 'Not Applicable'

Vehicle_1_Movement_ Preceding_Collision-Merging	Vehicle_1_Movement_Preceding_Collision-Merging = 'No'
	
	randommovement1 = random.choice (['Vehicle_1_Movement_Preceding_Collision-Stopped', 'Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight',
	'Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road',
	'Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn',
	'Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn',
	'Vehicle_1_Movement_Preceding_Collision-Making-U-Turn',
	'Vehicle_1_Movement_Preceding_Collision-Backing',
	'Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping',
	'Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle',
	'Vehicle_1_Movement_Preceding_Collision-Changing-Lanes',
	'Vehicle_1_Movement_Preceding_Collision-Parking-Manuever',
	'Vehicle_1_Movement_Preceding_Collision-Parked',
	'Vehicle_1_Movement_Preceding_Collision-Merging'])
	
	if randommovement1 is 'Vehicle_1_Movement_Preceding_Collision-Merging':
	    Vehicle_1_Movement_Preceding_Collision-Merging = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_1_Movement_Preceding_Collision-Merging = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Merging	Vehicle_2_Movement_Preceding_Collision-Merging = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Merging':
	Vehicle_2_Movement_Preceding_Collision-Merging = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Merging = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Merging = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Travelling-Wrong-Way	Vehicle_1_Movement_Preceding_Collision-Travelling-Wrong-Way = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Movement_Preceding_Collision-Travelling-Wrong-Way = 'Unknown'

Vehicle_2_Movement_Preceding_Collision-Travelling-Wrong-Way	Vehicle_2_Movement_Preceding_Collision-Travelling-Wrong-Way = 'No'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Movement_Preceding_Collision-Travelling-Wrong-Way = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Movement_Preceding_Collision-Travelling-Wrong-Way = 'Not Applicable'

Vehicle_1_Movement_Preceding_Collision-Other	Vehicle_1_Movement_Preceding_Collision-Other = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_2_Movement_Preceding_Collision-Other = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_2_Movement_Preceding_Collision-Other	Vehicle_2_Movement_Preceding_Collision-Other = 'No'
	
	randommovement2 = random.choice (['Vehicle_2_Movement_Preceding_Collision_Stopped', 'Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight', 'Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road', 'Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn', 'Vehicle_2_Movement_Preceding_Collision-Making-U-Turn', 'Vehicle_2_Movement_Preceding_Collision-Backing', 'Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping', 'Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle', 'Vehicle_2_Movement_Preceding_Collision-Changing-Lanes', 'Vehicle_2_Movement_Preceding_Collision-Parking-Manuever', 'Vehicle_2_Movement_Preceding_Collision-Entering-Traffic', 'Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning', 'Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane', 'Vehicle_2_Movement_Preceding_Collision-Parked', 'Vehicle_2_Movement_Preceding_Collision-Merging', 'Vehicle_2_Movement_Preceding_Collision-Other'])
	
	if randommovement2 is 'Vehicle_2_Movement_Preceding_Collision-Other':
	    Vehicle_2_Movement_Preceding_Collision-Other = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Movement_Preceding_Collision-Merging = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Movement_Preceding_Collision_Other = 'Not Applicable'

Vehicle_1_Type_of_Collision-Head-On	Vehicle_1_Type_of_Collision-Head-On = 'No'
	
	randomtype1 = random.choice (['Vehicle1TypeofCollisionHeadOn', 'Vehicle1TypeofCollisionSideSwipe', 'Vehicle1TypeofCollisionRearEnd', 'Vehicle1TypeofCollisionBroadside', 'Vehicle1TypeofCollisionHitObject', 'Vehicle1TypeofCollisionOther'])
	
	if randomtype1 is 'Vehicle_1_Type_of_Collision-Head-On':
	    Vehicle_1_Type_of_Collision-Head-On = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_1_Type_of_Collision-Head-On = 'Unknown'

Vehicle_2_Type_of_Collision-Head-On	Vehicle_2_Type_of_Collision-Head-On = 'No'
	
	randomtype2 = random.choice (['Vehicle2TypeofCollisionHeadOn', 'Vehicle2TypeofCollisionSideSwipe', 'Vehicle2TypeofCollisionRearEnd', 'Vehicle2TypeofCollisionBroadside', 'Vehicle2TypeofCollisionHitObject', 'Vehicle2TypeofCollisionVehiclePedestrian', 'Vehicle2TypeofCollisionOther'])
	
	if randomtype2 is 'Vehicle_2_Type_of_Collision_Head-On':
	    Vehicle_2_Type_of_Collision-Head-On = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Type_of_Collision-Head-On = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Type_of_Collision-Head-On = 'Not Applicable'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_1_Type_of_Collision-Side-Swipe	Vehicle_1_Type_of_Collision-Side-Swipe = 'No'
	
	randomtype1 = random.choice (['Vehicle1TypeofCollisionHeadOn', 'Vehicle1TypeofCollisionSideSwipe', 'Vehicle1TypeofCollisionRearEnd', 'Vehicle1TypeofCollisionBroadside', 'Vehicle1TypeofCollisionHitObject', 'Vehicle1TypeofCollisionOther'])
	
	if randomtype1 is 'Vehicle_1_Type_of_Collision_Side_Swipe':
	Vehicle_1_Type_of_Collision-Side-Swipe = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Type_of_Collision-Side-Swipe = 'Unknown'

Vehicle_2_Type_of_Collision-Side-Swipe	Vehicle_2_Type_of_Collision-Side-Swipe = 'No'
	
	randomtype2 = random.choice (['Vehicle2TypeofCollisionHeadOn', 'Vehicle2TypeofCollisionSideSwipe', 'Vehicle2TypeofCollisionRearEnd', 'Vehicle2TypeofCollisionBroadside', 'Vehicle2TypeofCollisionHitObject', 'Vehicle2TypeofCollisionVehiclePedestrian', 'Vehicle2TypeofCollisionOther'])
	
	if randomtype2 is 'Vehicle_2_Type_of_Collision-Side-Swipe':
	Vehicle_2_Type_of_Collision-Side-Swipe = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Type_of_Collision-Side-Swipe = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Type_of_Collision-Side-Swipe = 'Not Applicable'

Vehicle_1_Type_of_Collision-Rear-End	Vehicle_1_Type_of_Collision-Rear-End = 'No'
	
	randomtype1 = random.choice (['Vehicle1TypeofCollisionHeadOn', 'Vehicle1TypeofCollisionSideSwipe', 'Vehicle1TypeofCollisionRearEnd', 'Vehicle1TypeofCollisionBroadside', 'Vehicle1TypeofCollisionHitObject', 'Vehicle1TypeofCollisionOther'])
	
	if randomtype1 is 'Vehicle_1_Type_of_Collision-Rear-End':
	Vehicle_1_Type_of_Collision-Rear-End = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_1_Type_of_Collision-Rear-End = 'Unknown'

Vehicle_2_Type_of_Collision-Rear-End	Vehicle_2_Type_of_Collision-Rear-End = 'No'
	
	randomtype2 = random.choice (['Vehicle2TypeofCollisionHeadOn', 'Vehicle2TypeofCollisionSideSwipe', 'Vehicle2TypeofCollisionRearEnd', 'Vehicle2TypeofCollisionBroadside', 'Vehicle2TypeofCollisionHitObject', 'Vehicle2TypeofCollisionVehiclePedestrian', 'Vehicle2TypeofCollisionOther'])
	
	if randomtype2 is 'Vehicle_2_Type_of_Collision-Rear-End':
	Vehicle_2_Type_of_Collision-Rear-End = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	Vehicle_2_Type_of_Collision-Rear-End = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	Vehicle_2_Type_of_Collision-Rear-End = 'Not Applicable'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria

Vehicle_1_Type_of_Collision-Broadside	Vehicle_1_Type_of_Collision-Broadside = 'No'
	
	randomtype1 = random.choice (['Vehicle1TypeofCollisionHeadOn', 'Vehicle1TypeofCollisionSideSwipe', 'Vehicle1TypeofCollisionRearEnd', 'Vehicle1TypeofCollisionBroadside', 'Vehicle1TypeofCollisionHitObject', 'Vehicle1TypeofCollisionOther'])
	
	if randomtype1 is 'Vehicle_1_Type_of_Collision-Broadside':
	    Vehicle_1_Type_of_Collision-Broadside = 'Yes'
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_1_Type_of_Collision-Broadside = 'Unknown'

Vehicle_2_Type_of_Collision-Broadside	Vehicle_2_Type_of_Collision-Broadside = 'No'
	
	randomtype2 = random.choice (['Vehicle2TypeofCollisionHeadOn', 'Vehicle2TypeofCollisionSideSwipe', 'Vehicle2TypeofCollisionRearEnd', 'Vehicle2TypeofCollisionBroadside', 'Vehicle2TypeofCollisionHitObject', 'Vehicle2TypeofCollisionVehiclePedestrian', 'Vehicle2TypeofCollisionOther'])
	
	if randomtype2 is 'Vehicle_2_Type_of_Collision-Broadside':
	    Vehicle_2_Type_of_Collision-Broadside = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Type_of_Collision-Broadside = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Type_of_Collision-Broadside = 'Not Applicable'

Vehicle_1_Type_of_Collision-Hit-Object	Vehicle_1_Type_of_Collision-Hit-Object = 'No'
	
	randomtype1 = random.choice (['Vehicle1TypeofCollisionHeadOn', 'Vehicle1TypeofCollisionSideSwipe', 'Vehicle1TypeofCollisionRearEnd', 'Vehicle1TypeofCollisionBroadside', 'Vehicle1TypeofCollisionHitObject', 'Vehicle1TypeofCollisionOther'])
	
	if randomtype1 is 'Vehicle_1_Type_of_Collision-Hit-Object':
	    Vehicle_1_Type_of_Collision-Hit-Object = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_1_Type_of_Collision-Hit-Object = 'Unknown'

Vehicle_2_Type_of_Collision-Hit-Object	Vehicle_2_Type_of_Collision-Hit-Object = 'No'
	
	randomtype2 = random.choice (['Vehicle2TypeofCollisionHeadOn', 'Vehicle2TypeofCollisionSideSwipe', 'Vehicle2TypeofCollisionRearEnd', 'Vehicle2TypeofCollisionBroadside', 'Vehicle2TypeofCollisionHitObject', 'Vehicle2TypeofCollisionVehiclePedestrian', 'Vehicle2TypeofCollisionOther'])
	
	if randomtype2 is 'Vehicle_2_Type_of_Collision-Hit-Object':
	    Vehicle_2_Type_of_Collision-Hit-Object = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Type_of_Collision-Hit-Object = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Type_of_Collision-Hit-Object = 'Not Applicable'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria
Vehicle_1_Type_of_Collision-Overturned	Vehicle_1_Type_of_Collision-Overturned = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Type_of_Collision-Overturned = 'Unknown'

Vehicle_2_Type_of_Collision-Overturned	Vehicle_2_Type_of_Collision-Overturned = 'No'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Type_of_Collision-Overturned = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Type_of_Collision-Overturned = 'Not Applicable'

Vehicle_1_Type_of_Collision-Vehicle/Pedestrian	Vehicle_1_Type_of_Collision-Vehicle/Pedestrian = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vehicle_1_Type_of_Collision_Vehicle/Pedestrian = 'Unknown'

Vehicle_2_Type_of_Collision-Vehicle/Pedestrian	Vehicle_2_Type_of_Collision_Vehicle/Pedestrian = 'No'
	
	randomtype2 = random.choice (['Vehicle2TypeofCollisionHeadOn', 'Vehicle2TypeofCollisionSideSwipe', 'Vehicle2TypeofCollisionRearEnd', 'Vehicle2TypeofCollisionBroadside', 'Vehicle2TypeofCollisionHitObject', 'Vehicle2TypeofCollisionVehiclePedestrian', 'Vehicle2TypeofCollisionOther'])
	
	if randomtype2 is 'Vehicle_2_Type_of_Collision_Vehicle/Pedestrian':
	    Vehicle_2_Type_of_Collision_Vehicle/Pedestrian = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Type_of_Collision_Vehicle/Pedestrian = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Type_of_Collision_Vehicle/Pedestrian = 'Not Applicable'

Vehicle_1_Type_of_Collision-Other	Vehicle_1_Type_of_Collision-Other = 'No'
	
	randomtype1 = random.choice (['Vehicle1TypeofCollisionHeadOn', 'Vehicle1TypeofCollisionSideSwipe', 'Vehicle1TypeofCollisionRearEnd', 'Vehicle1TypeofCollisionBroadside', 'Vehicle1TypeofCollisionHitObject', 'Vehicle1TypeofCollisionOther'])
	
	if randomtype1 is 'Vehicle_1_Type_of_Collision-Other':
	    Vehicle_1_Type_of_Collision-Other = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Type_of_Collision-Other = 'Unknown'

Vehicle_2_Type_of_Collision-Other	Vehicle_2_Type_of_Collision-Other = 'No'
	
	randomtype2 = random.choice (['Vehicle2TypeofCollisionHeadOn', 'Vehicle2TypeofCollisionSideSwipe', 'Vehicle2TypeofCollisionRearEnd', 'Vehicle2TypeofCollisionBroadside', 'Vehicle2TypeofCollisionHitObject', 'Vehicle2TypeofCollisionVehiclePedestrian', 'Vehicle2TypeofCollisionOther'])
	
	if randomtype2 is 'Vehicle_2_Type_of_Collision-Other':
	    Vehicle_2_Type_of_Collision-Other = 'Yes'
	
	if Vehicle_1_Weather_Clear is 'Unknown':
	    Vehicle_2_Type_of_Collision-Other = 'Unknown'
	elif Vehicle_2_Weather_Clear is 'Not Applicable':
	    Vehicle_2_Type_of_Collision-Other = 'Not Applicable'

CVC_Sections_Violated_Cited	CVC_Sections_Violated_Cited = random.choice (['Yes', 'No', 'Unknown']) if Vehicle_1_Weather_Clear is 'Unknown': CVC_Sections_Violated_Cited = 'Unknown'

Table 4: Data Augmentation Criteria (continued)

Column Name	Augmentation Criteria
Vision_Obscurement	Vision_Obscurement = 'No' if Vehicle_1_Weather_Clear is 'Unknown': Vision_Obscurement = 'Unknown'
Inattention	Inattention = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': Inattention = 'Unknown'
Stop_and_Go_Traffic	Stop_and_Go_Traffic = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': Stop_and_Go_Traffic = 'Unknown'
Entering/Leaving_Ramp	Entering/Leaving_Ramp = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': Entering/Leaving_Ramp = 'Unknown'
Previous_Collision	Previous_Collision = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': Previous_Collision = 'Unknown'
Unfamiliar_With_Road	Unfamiliar_With_Road = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': Unfamiliar_With_Road = 'Unknown'
Defective_WEH_Equip_Cited	Defective_WEH_Equip_Cited = random.choice (['Yes', 'No', 'Unknown']) if Vehicle_1_Weather_Clear is 'Unknown': Defective_WEH_Equip_Cited = 'Unknown'
Uninvolved_Vehicle	Uninvolved_Vehicle = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': Uninvolved_Vehicle = 'Unknown'
Other	Other = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': Other = 'Unknown'
None_Apparent	None_Apparent = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': None_Apparent = 'Unknown'
Runaway_Vehicle	Runaway_Vehicle = random.choice (['Yes', 'No']) if Vehicle_1_Weather_Clear is 'Unknown': Runaway_Vehicle = 'Unknown'

	PDF_file_Number	Manufacturer_Name	Business_Name	Date_of_Accident	Time_of_Accident	Vehicle_1_Year	Vehicle_1_Make	Vehicle_1_Model	Vehicle
0	1 - Aimotive_091619	Aimotive Inc.	Aimotive Inc.	9/16/2019	10:00	2010	Toyota	Prius	Sto
1	2 - Apple_082418	Apple Inc.	Apple Inc.	8/24/2018	14:58	2016	Lexus	RX450h	I
2	3 - Apple_091919	Apple Inc.	Apple Inc.	9/19/2019	7:58	2017	Lexus	RX450h	Sto
3	4 - Apple_101518	Apple Inc.	Apple Inc.	10/15/2018	10:28	2017	Lexus	RX450h	I
4	5 - Aurora_011420	Aurora Innovation Inc.	Aurora	1/14/2020	11:13	2017	Lincoln	MKZ	Sto
...	...	...	...	...	...	...	...	...	
5251	5252-a	Jingchi Corp	Jingchi Corp	01/01/2016	18:27	2010	Lincoln	MKZ	Ur
5252	5253-a	Cruise Automation Inc.	Cruise Automation Inc.	11/10/2019	15:48	2012	Nissan	Leaf	Sto
5253	5254-a	Drive.ai Inc.	Drive.ai Inc.	11/04/2017	12:6	2018	Nissan	NV200 Taxi	Ur
5254	5255-a	Lyft Inc.	Lyft Inc.	08/13/2015	17:15	2010	Ford	Fusion Hybrid	Ur
5255	5256-a	Google Auto LLC	Google Auto LLC	08/03/2015	21:44	2011	Google	Self Driving Car	I

5256 rows × 140 columns

Figure 7: Augmented Data

6.2.3. Data Labelling, Classification, and Pre-Processing

The criteria for labelling the data is depicted in Figure 8.

```
# labelling data and saving them in a new column in the dataframe
new_column = np.where((dataframe['Vehicle_Driving_Mode']=='Autonomous Mode') |
                                          ((dataframe['Vehicle_Damage'] == 'Moderate')|
                                          (dataframe['Vehicle_Damage'] == 'Major') |
                                          (dataframe['Involved_in_Vehicle_1_Accident_Pedestrian'] == 'Yes') |
                                          (dataframe['Involved_in_Vehicle_1_Accident_Bicyclist'] == 'Yes') |
                                          (dataframe['Involved_in_Vehicle_1_Accident_Other'] == 'Yes') |
                                          (dataframe['Involved_in_Vehicle_2_Accident_Pedestrian'] == 'Yes') |
                                          (dataframe['Involved_in_Vehicle_2_Accident_Bicyclist'] == 'Yes') |
                                          (dataframe['Involved_in_Vehicle_2_Accident_Other'] == 'Yes') |
                                          (dataframe['Injured'] == 'Yes') |
                                          (dataframe['Injured_Driver'] == 'Yes') |
                                          (dataframe['Injured_Passenger'] == 'Yes') |
                                          (dataframe['Injured_Bicyclist'] == 'Yes')), '0', '1')
```

Figure 8: Criteria for Data Labelling

Upon labelling the data, a new classified column 'TrustMe' was created in the CSV file (see Appendix figure B9 for screen capture of the CSV data file) as shown in Figure 9. A snippet of dataset with TrustMe column is shown in Figure 10. This column stored the binary values where 1 is 'Trust' and 0 is 'Do Not Trust'. This classification of data was used by the model to predict whether to trust the autonomous vehicles or not.

```python
# Insert a new column 'TrustMe' if it doesnot already exists
if 'TrustMe' not in dataframe:
    dataframe.insert(loc=idx, column='TrustMe', value=new_column, allow_duplicates = False)

dataframe.to_csv(URL, index=False)
dataframe = pd.read_csv(URL)

# Display the dataset
dataframe
```

Figure 9: Code Snippet for adding New Classified Column TrustMe to the Dataset

	TrustMe	PDF_file_Number	Manufacturer_Name	Business_Name	Date_of_Accident	Time_of_Accident	Vehicle_1_Year	Vehicle_1_Make	Vehicle_1_Mode
0	1	1 - Aimotive_091619	Aimotive Inc.	Aimotive Inc.	9/16/2019	10:00	2010	Toyota	Priu
1	0	2 - Apple_082418	Apple Inc.	Apple Inc.	8/24/2018	14:58	2016	Lexus	RX450
2	1	3 - Apple_091919	Apple Inc.	Apple Inc.	9/19/2019	7:58	2017	Lexus	RX450
3	1	4 - Apple_101518	Apple Inc.	Apple Inc.	10/15/2018	10:28	2017	Lexus	RX450
4	1	5 - Aurora_011420	Aurora Innovation Inc.	Aurora	1/14/2020	11:13	2017	Lincoln	MK
...	...	...	...	...	...	...	...	...	...
5251	0	5252-a	Jingchi Corp	Jingchi Corp	01/01/2016	18:27	2010	Lincoln	MK
5252	0	5253-a	Cruise Automation Inc.	Cruise Automation Inc.	11/10/2019	15:48	2012	Nissan	Lea
5253	0	5254-a	Drive.ai Inc.	Drive.ai Inc.	11/04/2017	12:6	2018	Nissan	NV200 Ta
5254	0	5255-a	Lyft Inc.	Lyft Inc.	08/13/2015	17:15	2010	Ford	Fusion Hybri
5255	0	5256-a	Google Auto LLC	Google Auto LLC	08/03/2015	21:44	2011	Google	Self Driving Ca

5256 rows × 141 columns

Figure 10: Dataset with TrustMe Classified Column

Attributes of TrustMe column are mentioned in Table 6.

Table 5: Attributes of 'TrustMe' Column

Column Name	Description	Feature Type	Data Type
TrustMe	Labelled	Classification	Numerical

A seed of the random number generator was initialized to get repeatable results as shown in Figure 11.

```python
# Initializing the seed of the random number generator to get repeatable results

from numpy.random import seed
seed(0)
tf.random.set_seed(0)
```

Figure 11: Code Snippet for Initializing Random Number Generator

The dataset was then divided into train, validation, and test set at the ratio of 0.2 for validation and test set each and the rest as training set as shown in Figure 12. The training and validation data sets were used for designing the architecture, training the model, and hyperparameter optimization. The test set was used for reporting accuracy.

```
# Splitting the dataframe into train, validation and test sets

train, test = train_test_split(dataframe, test_size=0.2, shuffle=True, random_state=0)
train, val = train_test_split(train, test_size=0.2, shuffle=True, random_state=0)
print(len(train), 'samples in the training set')
print(len(val), 'samples in the validation set')
print(len(test), 'samples in the test set')
```

```
3363 samples in the training set
841 samples in the validation set
1052 samples in the test set
```

Figure 12: Code Snippet for Splitting Dataframe into Train, Validation, and Test Sets

Target value (TrustMe) or label was separated from the features by using dataframe.pop('TrustMe'). This target value or label was then used to train the model to make predictions. The dataframe was then wrapped with tf.data which enabled the use of feature columns as a bridge for mapping the columns in the Pandas dataframe to the features that are used train the model. The tf.data API enabled building of complex input pipelines from simple and reusable pieces. It also allowed large data handling, reading from different data formats, and performing complex transformations. The tf.data.Dataset abstraction was used which represented a sequence of elements wherein each element consisted of one or more components. It created a source dataset from the input data, applied transformations to preprocess the data and then iterated over the dataset and processed elements. The from_tensor_slices method from tf.data.Dataset was used to create a dataset whose elements were slices of the given tensors. Tensors are dataset elements, each component of which, has the same size in the first dimension. The tensors used were the dataframe dictionary which were sliced along their first dimension. This operation removed the first dimension of each tensor and used it as the dataset dimension in turn preserving the structure of the input tensors. Dataframe dictionary was used to preserve the column structure of the dataframe. The dataset was then shuffled (using buffer size of the length of the dataframe) to improve the training accuracy. Consecutive elements of the dataset were then combined into batches. These batches were divided into training, validation, and test datasets. From the input pipeline that was created, the dataset returned a dictionary of column names from the dataframe that mapped to the column values from rows in the dataframe as depicted in Figure 13. Outputs of every feature, batch of vehicle driving mode, batch of vehicle damage, batch of pedestrian involved in autonomous vehicle accident, batch of bicyclist involved in autonomous vehicle accident, batch of others involved in autonomous vehicle accident, batch of pedestrian involved in second vehicle accident, batch of bicyclist involved in second vehicle accident, batch of others involved in second vehicle accident, batch of injured, batch of injured driver, batch of injured passenger, batch of injured bicyclist and batch of TrustMe classified column are shown in Figures 14 through 27.

```python
# A utility method to create a tf.data dataset from a Pandas Dataframe
def df_to_dataset(dataframe, shuffle=True, batch_size=32):
  dataframe = dataframe.copy()
  labels = dataframe.pop('TrustMe')
  ds = tf.data.Dataset.from_tensor_slices((dict(dataframe), labels))
  if shuffle:
    ds = ds.shuffle(buffer_size=len(dataframe))
  ds = ds.batch(batch_size)
  return ds

batch_size = 100
train_ds = df_to_dataset(train, batch_size=batch_size)
val_ds = df_to_dataset(val, shuffle=True, batch_size=batch_size)
test_ds = df_to_dataset(test, shuffle=True, batch_size=batch_size)

for feature_batch, label_batch in train_ds.take(1):
  print('Every feature:', list(feature_batch.keys()))
  print('A batch of Vehicle Driving Mode:', feature_batch['Vehicle_Driving_Mode'])
  print('A batch of Vehicle Damage:', feature_batch['Vehicle_Damage'])
  print('A batch of Pedestrian involved in Vehicle 1 accident:', feature_batch['Involved_in_Vehicle_1_Accident_Pedestrian'])
  print('A batch of Bicyclist involved in Vehicle 1 accident:', feature_batch['Involved_in_Vehicle_1_Accident_Bicyclist'])
  print('A batch of Other involved in Vehicle 1 accident:', feature_batch['Involved_in_Vehicle_1_Accident_Other'])
  print('A batch of Pedestrian involved in Vehicle 2 accident:', feature_batch['Involved_in_Vehicle_2_Accident_Pedestrian'])
  print('A batch of Bicyclist involved in Vehicle 2 accident:', feature_batch['Involved_in_Vehicle_2_Accident_Bicyclist'])
  print('A batch of Other involved in Vehicle 2 accident:', feature_batch['Involved_in_Vehicle_2_Accident_Other'])
  print('A batch of Injured:', feature_batch['Injured'])
  print('A batch of Injured Driver:', feature_batch['Injured_Driver'])
  print('A batch of Injured Passenger:', feature_batch['Injured_Passenger'])
  print('A batch of Injured Bicyclist:', feature_batch['Injured_Bicyclist'])
  print('A batch of TrustMe:', label_batch)
```

Figure 13: Code Snippet of Method for Creating tf.data Dataset from Pandas Dataframe

```
Every feature: ['PDF_file_Number', 'Manufacturer_Name', 'Business_Name', 'Date_of_Accident', 'Time_of_Accident', 'V
ehicle_1_Year', 'Vehicle_1_Make', 'Vehicle_1_Model', 'Vehicle_1_was', 'Involved_in_Vehicle_1_Accident_Pedestrian',
'Involved_in_Vehicle_1_Accident_Bicyclist', 'Involved_in_Vehicle_1_Accident_Other', 'Number_of_vehicles_involved_wi
th_Vehicle_1', 'Vehicle_Damage', 'Damaged_Area', 'Vehicle_2_Year', 'Vehicle_2_Make', 'Vehicle_2_Model', 'Vehicle_2_
```

Figure 14: Output Snippet of Feature Batch

```
A batch of Vehicle Driving Mode: tf.Tensor(
[b'Conventional Mode' b'Autonomous Mode' b'Conventional Mode'
 b'Conventional Mode' b'Conventional Mode' b'Autonomous Mode'
```

Figure 15: Output Snippet of Batch of Vehicle Driving Mode

```
 b'Autonomous Mode'], shape=(100,), dtype=string)
A batch of Vehicle Damage: tf.Tensor(
[b'Moderate' b'Moderate' b'None' b'Minor' b'Minor' b'None' b'Minor'
 b'Minor' b'Minor' b'Minor' b'Moderate' b'Minor' b'Minor' b'Minor'
```

Figure 16: Output Snippet of Batch of Vehicle Damage

```
 b'Minor' b'Minor' b'None' b'Minor' b'unknown' b'Minor' b'Minor'], shape=(100,), dtype=string)
A batch of Pedestrian involved in Vehicle 1 accident: tf.Tensor(
[b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No'
 b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No'
```

Figure 17: Output Snippet of Batch of Pedestrian Involved in Autonomous Vehicle Accident

```
 b'No' b'No' b'No' b'No'], shape=(100,), dtype=string)
A batch of Bicyclist involved in Vehicle 1 accident: tf.Tensor(
[b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No'
 b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No'
```

Figure 18: Output Snippet of Batch of Bicyclist Involved in Autonomous Vehicle Accident

```
 b'No' b'No' b'No' b'No'], shape=(100,), dtype=string)
A batch of Other involved in Vehicle 1 accident: tf.Tensor(
[b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'Yes' b'No' b'No' b'No'
 b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'Yes' b'No' b'No' b'No' b'No'
```

Figure 19: Output Snippet of Batch of Others Involved in Autonomous Vehicle Accident

```
 b'No' b'No' b'No' b'No' b'No' b'No'], shape=(100,), dtype=string)
A batch of Pedestrian involved in Vehicle 2 accident: tf.Tensor(
[b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No'
 b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'not applicable' b'No' b'No'
```

Figure 20: Output Snippet of Batch of Pedestrians Involved in Second Vehicle Accident

```
 b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No'], shape=(100,), dtype=string)
A batch of Bicyclist involved in Vehicle 2 accident: tf.Tensor(
[b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No'
 b'No' b'No' b'No' b'No' b'No' b'No' b'Yes' b'not applicable' b'No' b'No'
```

Figure 21: Output Snippet of Batch of Bicyclist Involved in Second Vehicle Accident

```
 b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'No'], shape=(100,), dtype=string)
A batch of Other involved in Vehicle 2 accident: tf.Tensor(
[b'No' b'no' b'Yes' b'No' b'No' b'No' b'No' b'No' b'Yes' b'No' b'No' b'No'
 b'No' b'No' b'No' b'No' b'No' b'No' b'No' b'not applicable' b'No' b'No'
```

Figure 22: Output Snippet of Batch of Others Involved in Second Vehicle Accident

```
 b'No' b'No' b'No' b'No' b'No' b'No' b'Yes' b'No'], shape=(100,), dtype=string)
A batch of Injured: tf.Tensor(
[b'Yes' b'Unknown' b'Yes' b'Unknown' b'Unknown' b'Yes' b'Unknown'
 b'Unknown' b'Unknown' b'Unknown' b'Yes' b'Unknown' b'Yes' b'Unknown'
```

Figure 23: Output Snippet of Batch of Injured

```
 b'Unknown' b'Unknown' b'Unknown' b'Unknown' b'Unknown'], shape=(100,), dtype=string)
A batch of Injured Driver: tf.Tensor(
[b'No' b'Unknown' b'No' b'Unknown' b'Unknown' b'Yes' b'Unknown' b'Unknown'
 b'Unknown' b'Unknown' b'Yes' b'Unknown' b'Yes' b'Unknown' b'Unknown'
```

Figure 24: Output Snippet of Batch of Injured Driver

```
 b'Unknown' b'Unknown' b'Unknown'], shape=(100,), dtype=string)
A batch of Injured Passenger: tf.Tensor(
[b'No' b'Unknown' b'No' b'Unknown' b'Unknown' b'Yes' b'Unknown' b'Unknown'
 b'Unknown' b'Unknown' b'Yes' b'Unknown' b'Yes' b'Unknown' b'Unknown'
```

Figure 25: Output Snippet of Batch of Injured Passenger

```
 b'Unknown' b'Unknown'], shape=(100,), dtype=string)
A batch of Injured Bicyclist: tf.Tensor(
[b'No' b'Unknown' b'No' b'Unknown' b'Unknown' b'No' b'Unknown' b'Unknown'
 b'Unknown' b'Unknown' b'No' b'Unknown' b'No' b'Unknown' b'Unknown'
```

Figure 26: Output Snippet of Batch of Injured Bicyclist

```
 b'Unknown' b'Unknown' b'Unknown'], shape=(100,), dtype=string)
A batch of TrustMe: tf.Tensor(
[0 0 0 1 1 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0
 0 0 0 0 1 1 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 1 1 0 0 1 0 0 0 1
 0 0 1 0 0 0 0 1 0 0 0 1 0 1 0 0 1 0 1 1 0 1 0 0 0 0], shape=(100,), dtype=int32)
```

Figure 27: Output Snippet of Batch of TrustMe

Iterator was generated on the training dataset iterable object and was then run through the loop to return the next item in the sequence. This created a batch of feature columns. Categorical feature column was created to transform a batch of data. Since strings cannot be directly fed to the model, they were first mapped to numeric values. Categorical vocabulary columns provided a way to represent strings as a one-hot vector and were passed as a list using categorical_column_with_vocabulary_list. All the feature columns required to train the model were appended to the feature columns iterable as shown in figures 28 through 31 and the output is shown in figure 32.

```
# batch of feature columns
feature_column_batch = next(iter(train_ds))[0]
feature_columns = []

# A utility method to create a feature column and to transform a batch of data
def demo(feature_columns):

# indicator cols
  Involved_in_Vehicle_1_Accident_Pedestrian = feature_column.categorical_column_with_vocabulary_list(
     'Involved_in_Vehicle_1_Accident_Pedestrian', ['Yes', 'No'])
  Involved_in_Vehicle_1_Accident_Pedestrian_one_hot = feature_column.indicator_column(Involved_in_Vehicle_1_Accident_Pedestrian)
  feature_columns.append(Involved_in_Vehicle_1_Accident_Pedestrian_one_hot)

  Involved_in_Vehicle_1_Accident_Bicyclist = feature_column.categorical_column_with_vocabulary_list(
     'Involved_in_Vehicle_1_Accident_Bicyclist', ['Yes', 'No'])
  Involved_in_Vehicle_1_Accident_Bicyclist_one_hot = feature_column.indicator_column(Involved_in_Vehicle_1_Accident_Bicyclist)
  feature_columns.append(Involved_in_Vehicle_1_Accident_Bicyclist_one_hot)

  Involved_in_Vehicle_1_Accident_Other = feature_column.categorical_column_with_vocabulary_list(
     'Involved_in_Vehicle_1_Accident_Other', ['Yes', 'No'])
  Involved_in_Vehicle_1_Accident_Other_one_hot = feature_column.indicator_column(Involved_in_Vehicle_1_Accident_Other)
  feature_columns.append(Involved_in_Vehicle_1_Accident_Other_one_hot)
```

Figure 28: First Code Snippet of Iterable Feature Columns

```
  Involved_in_Vehicle_2_Accident_Pedestrian = feature_column.categorical_column_with_vocabulary_list(
     'Involved_in_Vehicle_2_Accident_Pedestrian', ['Yes', 'No', 'not applicable'])
  Involved_in_Vehicle_2_Accident_Pedestrian_one_hot = feature_column.indicator_column(Involved_in_Vehicle_2_Accident_Pedestrian)
  feature_columns.append(Involved_in_Vehicle_2_Accident_Pedestrian_one_hot)

  Involved_in_Vehicle_2_Accident_Bicyclist = feature_column.categorical_column_with_vocabulary_list(
     'Involved_in_Vehicle_2_Accident_Bicyclist', ['Yes', 'No', 'not applicable'])
  Involved_in_Vehicle_2_Accident_Bicyclist_one_hot = feature_column.indicator_column(Involved_in_Vehicle_2_Accident_Bicyclist)
  feature_columns.append(Involved_in_Vehicle_2_Accident_Bicyclist_one_hot)

  Involved_in_Vehicle_2_Accident_Other = feature_column.categorical_column_with_vocabulary_list(
     'Involved_in_Vehicle_2_Accident_Other', ['Yes', 'No', 'not applicable'])
  Involved_in_Vehicle_2_Accident_Other_one_hot = feature_column.indicator_column(Involved_in_Vehicle_2_Accident_Other)
  feature_columns.append(Involved_in_Vehicle_2_Accident_Other_one_hot)
```

Figure 29: Second Code Snippet of Iterable Feature Columns

```
Injured = feature_column.categorical_column_with_vocabulary_list(
    'Injured', ['Yes', 'No', 'Unknown'])
Injured_one_hot = feature_column.indicator_column(Injured)
feature_columns.append(Injured_one_hot)

Injured_Driver = feature_column.categorical_column_with_vocabulary_list(
    'Injured_Driver', ['Yes', 'No', 'Unknown'])
Injured_Driver_one_hot = feature_column.indicator_column(Injured_Driver)
feature_columns.append(Injured_Driver_one_hot)

Injured_Passenger = feature_column.categorical_column_with_vocabulary_list(
    'Injured_Passenger', ['Yes', 'No', 'Unknown'])
Injured_Passenger_one_hot = feature_column.indicator_column(Injured_Passenger)
feature_columns.append(Injured_Passenger_one_hot)

Injured_Bicyclist = feature_column.categorical_column_with_vocabulary_list(
    'Injured_Bicyclist', ['Yes', 'No', 'Unknown'])
Injured_Bicyclist_one_hot = feature_column.indicator_column(Injured_Bicyclist)
feature_columns.append(Injured_Bicyclist_one_hot)
```

Figure 30: Third Code Snippet of Iterable Feature Columns

```
  Vehicle_Damage = feature_column.categorical_column_with_vocabulary_list(
      'Vehicle_Damage', ['Minor', 'Moderate', 'Major', 'None'])
  Vehicle_Damage_one_hot = feature_column.indicator_column(Vehicle_Damage)
  feature_columns.append(Vehicle_Damage_one_hot)

  Vehicle_Driving_Mode = feature_column.categorical_column_with_vocabulary_list(
      'Vehicle_Driving_Mode', ['Autonomous Mode', 'Conventional Mode'])
  Vehicle_Driving_Mode_one_hot = feature_column.indicator_column(Vehicle_Driving_Mode)
  feature_columns.append(Vehicle_Driving_Mode_one_hot)

demo(feature_columns)
feature_columns
```

Figure 31: Fourth Code Snippet of Iterable Feature Columns

```
[IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Involved_in_Vehicle_1_Accident_Pedestrian', vocabulary_list=('Yes', 'No'), dtype=tf.st
ring, default_value=-1, num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Involved_in_Vehicle_1_Accident_Bicyclist', vocabulary_list=('Yes', 'No'), dtype=tf.str
ing, default_value=-1, num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Involved_in_Vehicle_1_Accident_Other', vocabulary_list=('Yes', 'No'), dtype=tf.string,
default_value=-1, num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Involved_in_Vehicle_2_Accident_Pedestrian', vocabulary_list=('Yes', 'No', 'not applica
ble'), dtype=tf.string, default_value=-1, num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Involved_in_Vehicle_2_Accident_Bicyclist', vocabulary_list=('Yes', 'No', 'not applicab
le'), dtype=tf.string, default_value=-1, num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Involved_in_Vehicle_2_Accident_Other', vocabulary_list=('Yes', 'No', 'not applicabl
e'), dtype=tf.string, default_value=-1, num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Injured', vocabulary_list=('Yes', 'No', 'Unknown'), dtype=tf.string, default_value=-1,
num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Injured_Driver', vocabulary_list=('Yes', 'No', 'Unknown'), dtype=tf.string, default_va
lue=-1, num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Injured_Passenger', vocabulary_list=('Yes', 'No', 'Unknown'), dtype=tf.string, default
_value=-1, num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Injured_Bicyclist', vocabulary_list=('Yes', 'No', 'Unknown'), dtype=tf.string, default
_value=-1, num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Vehicle_Damage', vocabulary_list=('Minor', 'Moderate', 'Major', 'None'), dtype=tf.stri
ng, default_value=-1, num_oov_buckets=0)),
 IndicatorColumn(categorical_column=VocabularyListCategoricalColumn(key='Vehicle_Driving_Mode', vocabulary_list=('Autonomous Mode', 'Conventional Mode'), dtype
=tf.string, default_value=-1, num_oov_buckets=0))]
```

Figure 32: Output of Iterable Feature Columns

Once the feature columns were defined, a feature layer was created using DenseFeatures which produced a dense Tensor to be used as input to the Keras model as shown in figure 33.

```
# Creating feature layer
feature_layer = tf.keras.layers.DenseFeatures(feature_columns)
print(feature_layer(feature_column_batch).numpy()[0])
```

```
[1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 1. 0. 1.]
```

Figure 33: Feature Layer Creation

6.2.4. Developing Sequential ANN Model

The feature layer created earlier was used to build a linear sequential Keras model where the layers were stacked on top of each other (figure 34). Layers are the basic building blocks of neural networks and they extract representations of the data that is fed into them. input_shape argument was used to provide shape tuple to the first Dense layer so that the model receives information about its input shape. This first layer with the input shape was then used by the following layers as automatic shape inference. The first two layers were densely connected hidden layers with 32 hidden units (nodes or neurons), and third layer was an output layer that returned a single continuous value. Rectified Linear Unit (relu) activation function was used for first two layers since it is linear for positive values and zero for negative values. Linear activation function was used for the output layer for numerical stability. This model had two hidden layers between input and output where the output referred to the amount of freedom that the network was allowed when learning an internal representation. Smaller number of hidden units and layers were chosen to avoid the network from learning complex representations and unwanted patterns in turn preventing overfitting of training data.

```
# Creating a sequential model and adding layers
model = tf.keras.Sequential([
  feature_layer,
  tf.keras.layers.Dense(32, activation='relu',input_shape=train.shape[2:]),
  tf.keras.layers.Dense(32, activation='relu'),
  tf.keras.layers.Dense(1, activation='linear'),
])
```

Figure 34: Creating a Sequential Model and Adding Layers

6.2.5. Model Training, Predictions and Performance

The model was configured to use optimizer and loss function for training. binary_crossentropy loss function was used since this was a binary classification problem where the model output was a probability of single-unit layer with linear activation along with adam (a stochastic optimization method) optimizer. Accuracy metrics was used for judging the performance of the model. The model was trained on Numpy arrays of input data and labels by passing the training dataset to model's fit function.

The number of epochs or the iterations on dataset were set to 15. This was stored in a history object which is a dictionary that recorded and returned training loss and accuracy values and validation loss and validation accuracy values at each successive epoch. The training loss decreased with each epoch and the training accuracy increased with each epoch. This was expected since gradient descent optimization was used which was supposed to minimize the desired quantity on every iteration.

During the model training, current state of the model at each step of the training algorithm was evaluated. Both training loss and validation loss decreased with the increasing number of epochs. There was a sudden drop in the training loss between 6th and 7th epoch and a sudden drop of validation loss between 5th and 6th epoch. After 8th epoch, the difference between the rate at which training loss decreased and the rate at which the validation loss decreased was minimal. At 7th epoch, the model had an accuracy of 98.45% and 98.57% on validation set which means that the model performed with the accuracy of close of 98.57%. Although, this validation accuracy decreased by 0.05% on the 8th epoch but increased again in the 9th epoch to 99.88% and by the 10th epoch, the validation accuracy was 100%. Between 11th and 12th epoch, the training accuracy fluctuated a little bit but finally stabilized at the 14th epoch and increased on the 15th epoch while the validation accuracy was still at a 100%. This meant that the model was fitting the training set better while still retaining its ability to predict on new data and was generalizing the data properly. Model compilation, training and model summary is depicted in Figure 35 and the epochs are depicted in Figures 36 through 38 and model summary output is shown in Figure 39.

```
# Compiling the model
model.compile(
     loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
     optimizer='adam',
     metrics=['accuracy'])

# Training the model
history = model.fit(train_ds,
           validation_data=val_ds,
           epochs=15)

# Model summary
model.summary()
```

Figure 35: Model Compiling, Training, and Model Summary

```
Epoch 1/15
34/34 [==============================] - 4s 106ms/step - loss: 0.4853 - accuracy: 0.9619 - val_loss: 0.0000e+00 - val_accuracy: 0.
0000e+00
Epoch 2/15
34/34 [==============================] - 1s 25ms/step - loss: 0.1529 - accuracy: 0.9726 - val_loss: 0.1003 - val_accuracy: 0.9786
Epoch 3/15
34/34 [==============================] - 1s 25ms/step - loss: 0.1032 - accuracy: 0.9726 - val_loss: 0.0732 - val_accuracy: 0.9786
Epoch 4/15
34/34 [==============================] - 1s 25ms/step - loss: 0.0763 - accuracy: 0.9726 - val_loss: 0.0552 - val_accuracy: 0.9786
Epoch 5/15
34/34 [==============================] - 1s 26ms/step - loss: 0.0562 - accuracy: 0.9726 - val_loss: 0.0428 - val_accuracy: 0.9786
```

Figure 36: Epochs 1-5

```
Epoch 6/15
34/34 [==============================] - 1s 31ms/step - loss: 0.0406 - accuracy: 0.9750 - val_loss: 0.0296 - val_accuracy: 0.9857
Epoch 7/15
34/34 [==============================] - 1s 25ms/step - loss: 0.0271 - accuracy: 0.9845 - val_loss: 0.0208 - val_accuracy: 0.9857
Epoch 8/15
34/34 [==============================] - 1s 27ms/step - loss: 0.0203 - accuracy: 0.9911 - val_loss: 0.0143 - val_accuracy: 0.9952
Epoch 9/15
34/34 [==============================] - 1s 23ms/step - loss: 0.0155 - accuracy: 0.9955 - val_loss: 0.0107 - val_accuracy: 0.9988
Epoch 10/15
34/34 [==============================] - 1s 23ms/step - loss: 0.0119 - accuracy: 0.9988 - val_loss: 0.0081 - val_accuracy: 1.0000
```

Figure 37: Epochs 6-10

```
Epoch 11/15
34/34 [==============================] - 1s 25ms/step - loss: 0.0092 - accuracy: 0.9994 - val_loss: 0.0074 - val_accuracy: 1.0000
Epoch 12/15
34/34 [==============================] - 1s 26ms/step - loss: 0.0078 - accuracy: 0.9997 - val_loss: 0.0056 - val_accuracy: 1.0000
Epoch 13/15
34/34 [==============================] - 1s 25ms/step - loss: 0.0065 - accuracy: 0.9994 - val_loss: 0.0041 - val_accuracy: 1.0000
Epoch 14/15
34/34 [==============================] - 1s 23ms/step - loss: 0.0058 - accuracy: 0.9994 - val_loss: 0.0038 - val_accuracy: 1.0000
Epoch 15/15
34/34 [==============================] - 1s 22ms/step - loss: 0.0049 - accuracy: 0.9997 - val_loss: 0.0034 - val_accuracy: 1.0000
```

Figure 38: Epochs 11-15

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_features (DenseFeature multiple                  0         
_________________________________________________________________
dense (Dense)                multiple                  1088      
_________________________________________________________________
dense_1 (Dense)              multiple                  1056      
_________________________________________________________________
dense_2 (Dense)              multiple                  33        
=================================================================
Total params: 2,177
Trainable params: 2,177
Non-trainable params: 0
_________________________________________________________________
```

Figure 39: Model Summary

Training and validation loss curves were plotted as shown in Figure 40. Training learning curve helped evaluate training dataset to understand how well the model was learning. Validation learning curve helped evaluate validation dataset to understand how well the model was generalizing. Both the train learning and validation learning curves were plotted on the same graph. From the graph it is evident that after 10^{th} epoch, both the curves began to converge and the training and validation losses decreased to a point of stability with a minimal gap between those two final loss values which indicated that the model is a good fit.

```
# Plot the training and validation loss curves
plt.plot(history.history["loss"], label="Training Loss")
plt.plot(history.history["val_loss"], label="Validation Loss")
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.show()
```

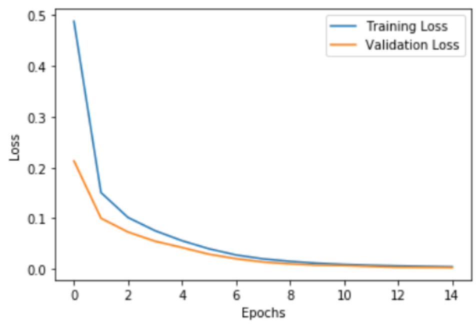

Figure 40: Plot of Training and Validation Loss Curves

Training and validation accuracy curves were also plotted on the same graph as depicted in Figure 41. The graph showed good performance on validation data as opposed to training data. Trends for both training and validation accuracy increased initially and then stabilized around 10^{th} epoch after which the curves began to converge with a minimal gap between those two final accuracy values indicating that the model is a good fit.

```
# Plot the training and validation accuracy curves
plt.plot(history.history["accuracy"], label="Training Accuracy")
plt.plot(history.history["val_accuracy"], label="Validation Accuracy")
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.show()
```

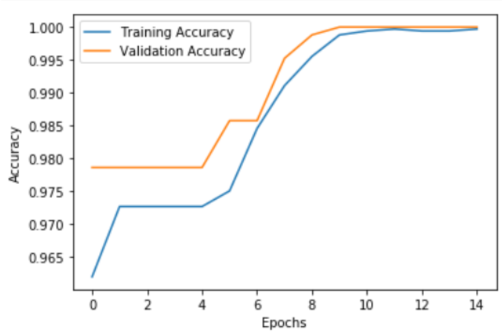

Figure 41: Plot of Training and Validation Accuracy Curves

Upon training the model, it was evaluated with test data and a test accuracy of 100% was achieved as shown in Figure 42.

```
# Evaluating the model on the test set
test_loss, test_accuracy = model.evaluate(test_ds)

print('\n\nTest Loss {}, Test Accuracy {}'.format(test_loss, test_accuracy))
```

```
11/11 [==============================] - 0s 15ms/step - loss: 0.0036 - accuracy: 1.0000


Test Loss 0.003612868434918875, Test Accuracy 1.0
```

Figure 42: Evaluating the Model on Test Set

Predictions were made on the trained model which indicated higher percentages of diminished trust in autonomous vehicle technology as shown in Figure 43.

```
predictions = model.predict(test_ds)

# Show some results
for prediction, TrustMe in zip(predictions[:10], list(test_ds)[0][1][:10]):
  print("Predicted trust: {:.2%}".format(tf.nn.sigmoid(prediction[0])*100),
        " | Actual outcome: ",
        ("Trust" if bool(TrustMe) else "Do Not Trust"))

prob = tf.nn.sigmoid(prediction[0])

print(
     "Autonomous vehicles" % (100 * prob)
)
```

```
Predicted trust: 96.33%  | Actual outcome:  Do Not Trust
Predicted trust: 0.00%  | Actual outcome:  Do Not Trust
Predicted trust: 0.00%  | Actual outcome:  Do Not Trust
Predicted trust: 2.20%  | Actual outcome:  Do Not Trust
Predicted trust: 0.00%  | Actual outcome:  Do Not Trust
Predicted trust: 0.00%  | Actual outcome:  Do Not Trust
Predicted trust: 0.01%  | Actual outcome:  Do Not Trust
Predicted trust: 9742.13%  | Actual outcome:  Do Not Trust
Predicted trust: 0.00%  | Actual outcome:  Do Not Trust
Predicted trust: 129.40%  | Actual outcome:  Do Not Trust
Autonomous vehicles
```

Figure 43: Predictions Made on Trained Model

6.3. Trust, Intention and Anti-Autonomy

Anti-autonomous nature of autonomous vehicle is exhibited by its unexpected driving behavior on the road. While human drivers can exercise their cognitive and intuitive abilities and react to unprecedented situations while driving, autonomous vehicles often lack similar abilities which causes them to behave irrationally and leads to collisions. Erratic behavior of autonomous vehicles is counted as its anti-autonomous nature and is subject to judgement until these vehicles are incorporated with skills, ethics, morals, and emotions akin humans. This generates an inversely proportional relationship between trust and anti-autonomy (Figure 44). When autonomous vehicles are involved in accidents, irrespective of whoever is at fault, it declines overall trust in them since it recalls risk and safety factors. Instabilities in autonomous vehicle operations also cause trust to decline and increases risk of damages to property and human life, thus creating an inversely proportional relationship between trust and risk (Figure 44). However, since the autonomous vehicles are designed with the insertion of myriad of technological and safety features, it helps build a directly proportional relationship of trust with safety (Figure 44).

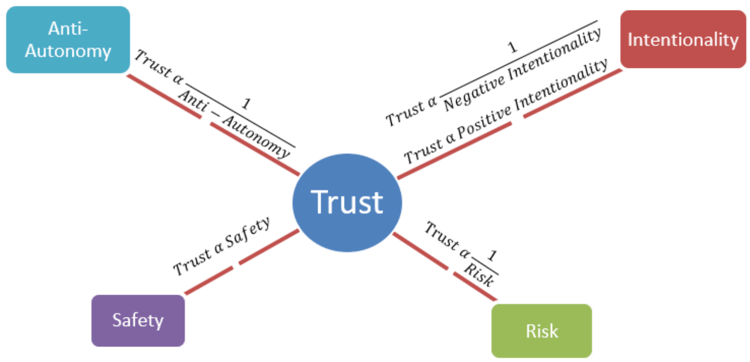

Figure 44: Relationship between Trust, Anti-Autonomy, Intentionality, Safety and Risk

Inclusion of higher levels of safety features in terms of advanced driver assistance systems also corroborates with intentionality of manufacturers for promoting trust in autonomous vehicles, thus creating a directly proportional relationship of trust with positive intentionality (Figure 44). It has been observed that trust affects acceptance, utilization and reliance and has been considered a key determining factor of the intention to use autonomous vehicle [6]. Intentionality has been an argumentative multidirectional concept as it not only brings forth the positive intentions of manufacturers striving to promote trust, but also the intentions of people in terms of adopting and owning autonomous vehicles. Yet another dimension is the intention of the autonomous vehicle on the road while operating in autonomous driving mode. Even though autonomous vehicles have logged countless hours and millions of miles of safe operation on roads, there still are situations where drivers sitting inside them have had to take control of the vehicle in dubious situations of collisions, unfavorable weather conditions and construction zones. Drivers behind the wheel in these situations mentioned their discomfort as it was evident in the autonomous vehicles' disengagement reports provided by California DMV [9]. Driver's discomfort could also be linked to his/her sudden engagement in taking control after a period of lack of attention due to overreliance on vehicle automation. These disengagement reports accounted and reported the situations in which the autonomous control of the car operations was taken over by the human driver to take control. Apart from the discomfort of the driver sitting in the autonomous vehicle geared up to disengage and take control, drivers of other vehicle sharing the road may also have their fair share of discomfort sharing the roads with autonomous vehicles.

Relationship between trust, intentionality, anti-autonomy, risk, and safety was precisely explained and clarified from the reference point of the NoTrust model and the data analysis of the collision dataset. Since the dataset used to build and train the model accounts for reports of traffic collisions involving autonomous vehicles, records with vehicles operating in autonomous driving mode which involved vehicle damage greater than minor and involved pedestrian/bicyclist injuries or damages was flagged as unsafe and not to be trusted.

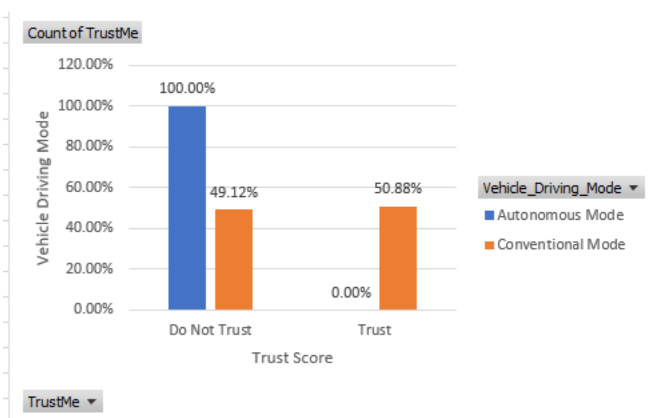

Figure 45: Graph of Vehicle Driving Mode with Trust Score

100% vehicles driving in autonomous mode (given the fact that all of the collision reports involved autonomous vehicles) and 49.12% vehicles which were initially driving in the autonomous mode and drivers had to later disengage and take control to drive in conventional mode were found not be trusted due to the intensity of reported injuries and damages (Figure 45).

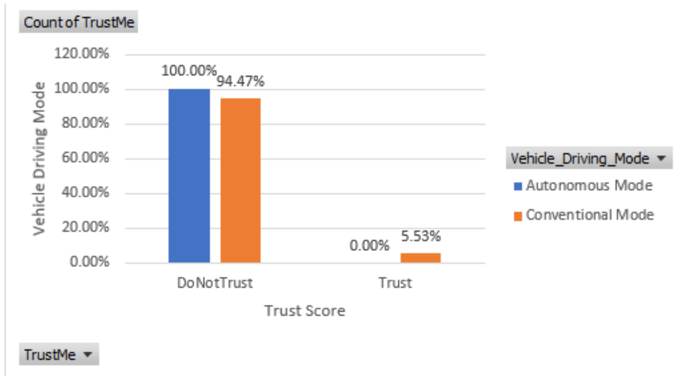

Figure 46: Graph of Vehicle Driving Mode with Trust Score (after Data Augmentation)

Upon data augmentation, 100% vehicles driving in autonomous mode and 94.47% vehicles which were initially driving in the autonomous mode and drivers had to later disengage and take control to drive in conventional mode were found not be trusted due to the intensity of reported injuries and damages (Figure 46). This also results in a perception of autonomous vehicles to be unsafe and risky and hence support the analogy of inversely proportional relationship of trust with risk and a directly proportional relationship of trust with safety implying reduced trust due to reduced safety.

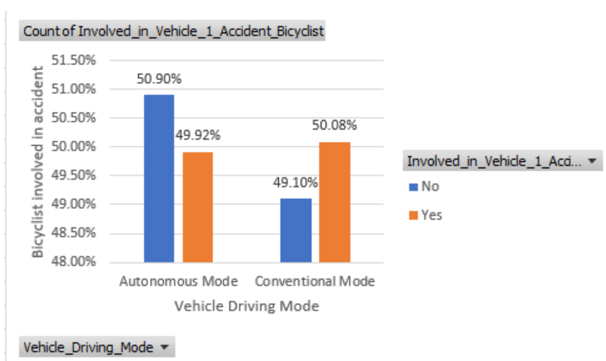

Figure 47: Graph of Vehicle Driving Mode and Bicyclist Involved in Accident

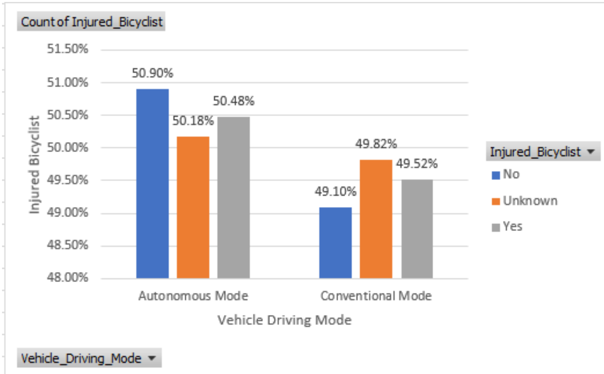

Figure 48: Graph of Vehicle Driving Mode and Injured Bicyclist

Collisions caused by vehicle driving in autonomous mode which involved bicyclists were 49.92% where bicyclist were injured in 50.48% collisions (Figures 47 and 48). Collisions caused by vehicle driving in conventional mode which involved bicyclists were 50.08% where bicyclist were injured in 49.52% collisions (Figures 48 and 49).

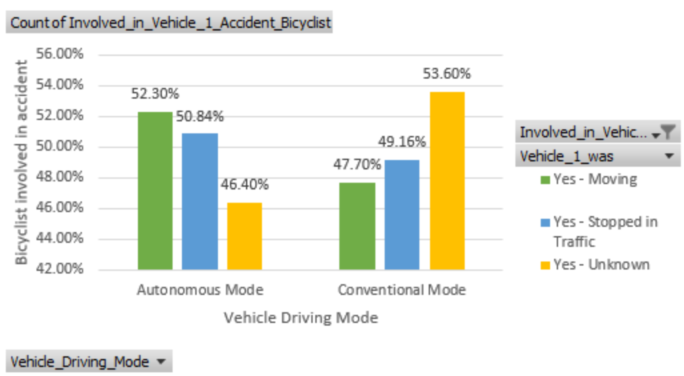

Figure 49: Graph of Vehicle Driving Mode and Bicyclist Involved in Accident when Vehicle was Moving/Stopped in Traffic

From the collisions which involved bicyclist when vehicle was driving in autonomous mode, vehicle was moving in 52.30% collisions and was stopped in traffic in 50.84% collisions whereas when vehicle was driving in conventional mode, vehicle was moving in 47.70% collisions and was stopped in traffic in 49.16% collisions (Figure 49). These results support the analogy of inversely proportional relationship of trust with anti-autonomy and negative intentionality.

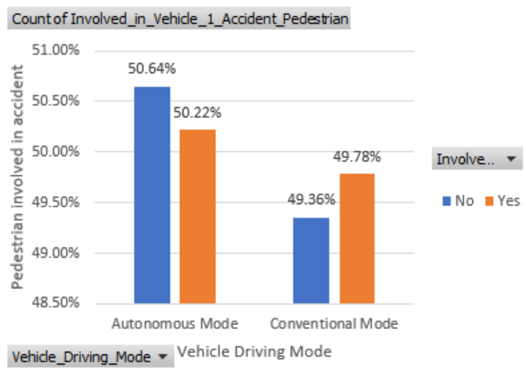

Figure 50: Graph of Vehicle Driving Mode and Pedestrian Involved in Accident

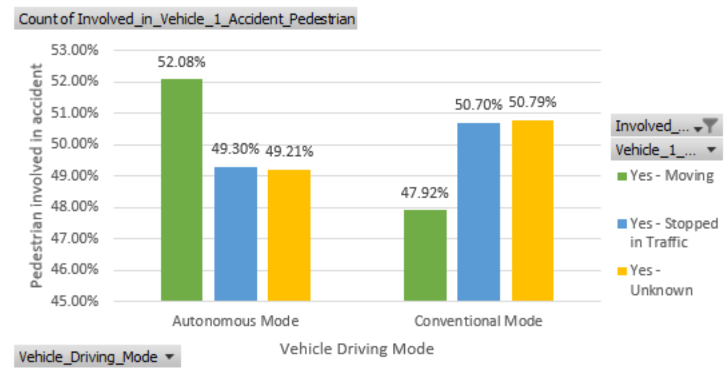

Figure 51: Graph of Vehicle Driving Mode and Pedestrian Involved in Accident when Vehicle was Moving/Stopped in Traffic

Collisions which involved pedestrian and were caused by vehicle driving in autonomous mode were 50.22% whereas those caused by vehicle driving in conventional mode were 49.78% (Figure 50). From the collisions which involved pedestrian when vehicle was driving in autonomous mode, vehicle was moving in 52.08% collisions and was stopped in traffic in 49.30% collisions whereas those caused by vehicle driving in conventional mode, vehicle was moving in 47.92% collisions and was stopped in traffic in 50.70% collisions (Figure 51).

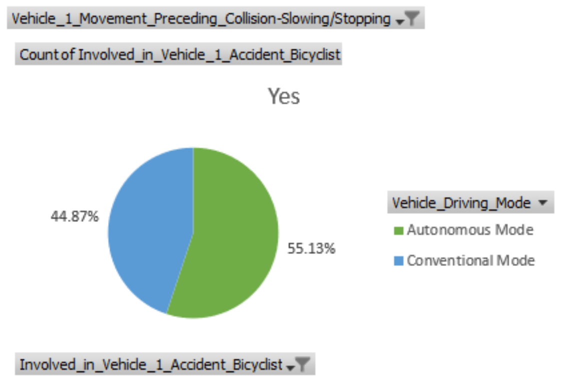

Figure 52: Graph of Bicyclist Involved in Accident when Vehicle's Movement Preceding Collision was Slowing/Stopping

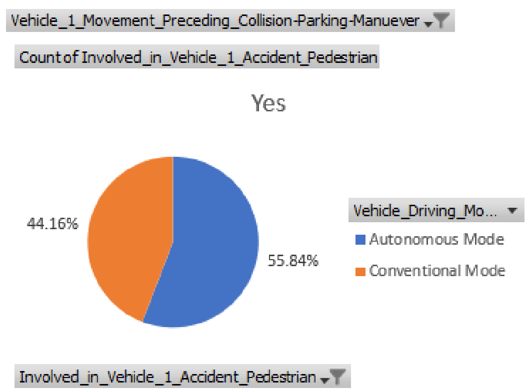

Figure 53: Graph of Pedestrian Involved in Accident when Vehicle's Movement Preceding Collision was Parking Maneuver

It was observed that moving and stopped in traffic state of the vehicle while driving in autonomous mode still caused collisions involving pedestrian and bicyclist, and some other cars or objects. This could be indicative of the fact that behavior and actions of the autonomous vehicle while sharing the roads with others are often perceived to be perplexing. This perplexing behavior often produces a perception of anti-autonomous nature of autonomous vehicles in the minds of other drivers sharing the road. This belief is strengthened by the analysis of the impact of preceding movements on the collisions which revealed that slowing/stopping movement caused by the vehicle operating in autonomous mode which also involved bicyclist led to 55.13% collisions as compared to 44.87% collisions caused when vehicle was operating in conventional mode and had a slowing/stopping preceding movement (Figure 52). However, slowing/stopping preceding movement did not have significant impact on pedestrian involved in these collisions. On the contrary, parking maneuver movement preceding collisions caused by the vehicle operating in autonomous mode which also involved pedestrian were 55.84% as compared to 44.16% collisions caused when vehicle was operating in conventional mode and had a parking maneuver preceding collision (Figure 53). Parking maneuver preceding movement did not have significant impact on bicyclist involved in these collisions. These results support the analogy of inversely proportional relationship of trust with anti-autonomy and negative intentionality.

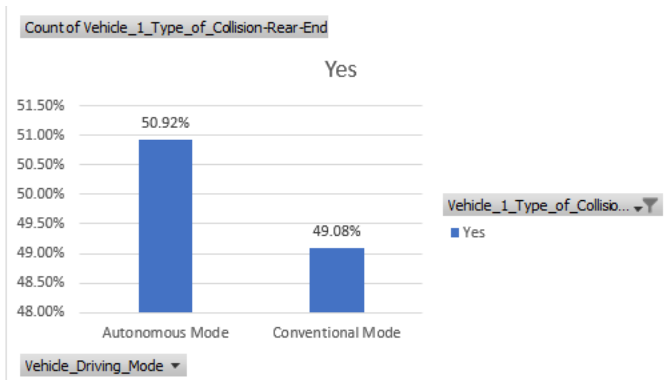

Figure 54: Graph of Vehicle Driving Mode and Rear End Collision

Elusive actions and behavior of the autonomous vehicle when stopping at an intersection were evidently expressed in the analysis of the type of collision autonomous vehicle sustained while driving in autonomous mode. The results confirmed that in 50.92% of collisions when vehicle was driving in autonomous mode, autonomous vehicle sustained rear-end collision as opposed to 49.08% collisions when vehicle was driving in conventional mode (Figure 54). This also supports the analogy of inversely proportional relationship of trust with anti-autonomy and negative intentionality.

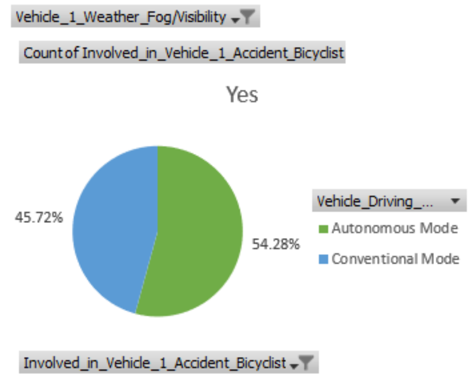

Figure 55: Graph of Bicyclist Involved in Accident during Fog/Visibility Weather Condition

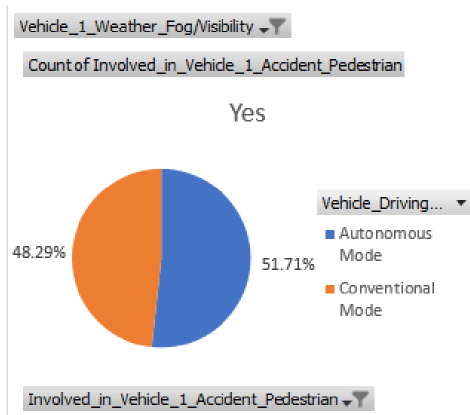

Figure 56: Graph of Pedestrian Involved in Accident during Fog/Visibility Weather Condition

Analysis of the impact of weather conditions on the collisions revealed that collisions during fog/visibility weather condition caused by the vehicle operating in autonomous mode which also involved bicyclist were 54.28% as compared to 45.72% collisions caused when vehicle was operating in conventional mode during the same fog/visibility weather condition (Figure 55). Likewise, collisions during fog/visibility weather condition caused by the vehicle operating in autonomous mode which also involved pedestrian were 51.71% as compared to 48.29% collisions caused when vehicle was operating in conventional mode during the same fog/visibility weather condition (Figure 56). This indicated that foggy weather conditions with limited visibility led to significant amount of collisions involving pedestrians and bicyclist when vehicle was operating in autonomous mode. These results support the analogy of inversely proportional relationship of trust with anti-autonomy, negative intentionality and risk and propose higher amounts of associated safety concerns leaning towards a decline in trust.

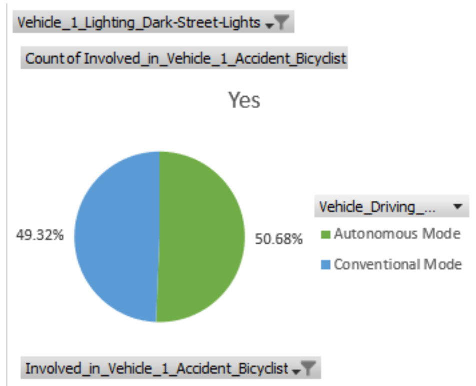

Figure 57: Graph of Bicyclist Involved in Accident during Dark Street Lights Lighting Condition

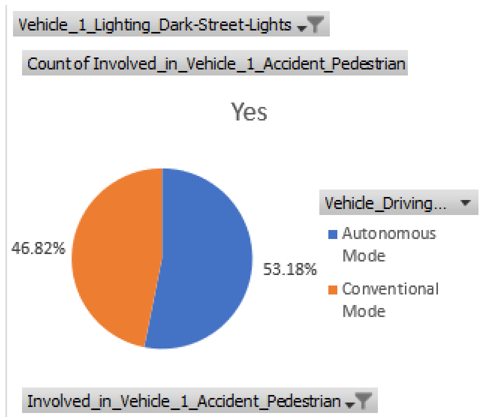

Figure 58: Graph of Pedestrian Involved in Accident during Dark Street Lights Lighting Condition

Analysis of the impact of lighting conditions on the collisions revealed that collisions at night with street lights on caused by the vehicle operating in autonomous mode which also involved bicyclist were 50.68% as compared to 49.32% collisions caused when vehicle was operating in conventional mode at night with street lights on (Figure 57). Likewise, collisions at night with street lights on caused by the vehicle operating in autonomous mode which also involved pedestrian were 53.18% as compared to 46.82% collisions caused when vehicle was operating in conventional mode at night with street lights on (Figure 58). This indicated that higher number of collisions happening at night when vehicle was operating in autonomous mode involved pedestrians. These results support the analogy of inversely proportional relationship of trust with anti-autonomy, negative intentionality and risk and propose higher amounts of associated safety concerns leaning towards a decline in trust.

6.4. References

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CHAPTER 7. CONCLUSION

Autonomous vehicles are not yet functionally equipped to comprehend and analyze behavior and intention of human drivers. This befalls them into tricks of human drivers and compromises their internal systems into often harming themselves or the drivers, pedestrians, and bicyclists, or hitting objects around them. Unfavorable weather conditions, road surface conditions and lighting conditions also often impact safe operations of autonomous vehicles. Nevertheless, this nature of these vehicles very well works in conjunctions with the laws of robotics yet falls short in putting forth the best of the autonomous vehicle functionality, convenience, and usefulness. The unpredictability of autonomous vehicles during unprecedented roadway conditions, abrupt driving behavior of human drivers, and sudden appearance of moving objects in front of them often leads them into collisions and highlights their anti-autonomous capabilities. A strong urge to effectively help study, analyze, understand, and explain the reason behind the anti-autonomous trait of autonomous vehicles fueled the inspiration for this research work. This led to the goal of advancing the state of the art in anti-autonomy via the development and validation of the anti-autonomy model.

Autonomous vehicles were launched with a promise to deliver safe and secure driving environment while minimizing traffic congestions, however, collision reports involving autonomous vehicles provided by the California DMV painted a different picture. Collision reports involving autonomous vehicles from October 2014 to March 2020 (which is the latest reported data) was utilized to present an innovative anti-autonomy NoTrust ANN model. This data was augmented, labelled, classified, and pre-processed and then applied towards the creation of NoTrust model using linear sequential model libraries in Keras over Tensorflow. NoTrust model was then used to predict trust in autonomous vehicles. Trained model was able to achieve a 100%

accuracy which was evident in the results of the model compilation and training, plots of validation and training accuracies and losses. Model evaluations and predictions made were used to comprehend the characteristics of trust, intention and anti-autonomy and helped establish a relationship between them. It also aided a sketch of inter-dependencies between trust, intentionality, anti-autonomy, risk, and safety. Furthermore, this dissertation demonstrated an extensive analysis of the original collision reports data and augmented data in terms of illustrations of the impact of several contributing factors of collisions such as vehicle driving mode, damages sustained by the vehicle, pedestrian and bicyclist involved in collisions, weather conditions, roadway surface, lighting conditions, movement of vehicle preceding collision and type of collisions. Following interpretations were drawn from the evaluation of the NoTrust model, predictions, and a thorough analysis of the collision data reports –

- Inability of the autonomous vehicle to communicate to the human driver to disengage and take control just in time
- Unclear intentions of autonomous vehicle in its ability to handle the situation resulting in confusion for the pedestrian/bicyclist on the road
- Pedestrian/bicyclist misunderstanding sudden brake intervention by the autonomous vehicle
- Unclear intentions of the autonomous vehicle in its ability to engage brakes upon encountering pedestrians/bicyclist
- Pedestrian/Bicyclist/other vehicles obliviously paralyzing the sensor mechanics of the autonomous vehicle while trying to understand the actions of the vehicle
- Complex decision making capabilities of the autonomous vehicle architecture in the event of sudden appearance of pedestrian/bicyclist in front of them

- Elusive actions and behavior of the autonomous vehicle when stopping at an intersection
- Autonomous vehicle being over cautious
- Evaluation of the NoTrust model and predictions supported the analogy of inversely proportional relationship of trust with anti-autonomy, negative intentionality and risk and proposed higher amounts of associated safety concerns leaning towards a decline in trust
- Inclusion of higher levels of safety features in terms of advanced driver assistance systems corroborated with intentionality of manufacturers for promoting trust in autonomous vehicles and encouraged a directly proportional relationship of trust with positive intentionality
- Analysis of collision data on injuries and vehicle damage caused a perception of autonomous vehicles to be unsafe and risky and hence supported the analogy of inversely proportional relationship of trust with risk and a directly proportional relationship of trust with safety implying reduced trust due to reduced safety
- Analysis of collisions which involved bicyclist when vehicle was driving in autonomous mode versus conventional mode supported the analogy of inversely proportional relationship of trust with anti-autonomy and negative intentionality
- Analysis of collisions involving pedestrian and bicyclist, caused by autonomous vehicle when moving or stopped in traffic state while operating in autonomous mode, impact of slowing/stopping preceding movements prior to collisions, parking maneuver, foggy weather conditions with limited visibility and vehicle operating on dark street with street lights on, supported the analogy of inversely proportional relationship of trust with anti-autonomy, negative intentionality and risk and proposed higher amounts of associated safety concerns leaning towards a decline in trust

- Analysis of rear-end collisions sustained by the autonomous vehicle uncovered its elusive actions and behavior when stopping at an intersection which supported the analogy of inversely proportional relationship of trust with anti-autonomy and negative intentionality.

The inception, concept and evolution of autonomous vehicles envisions a delivery of safety benefits. Autonomous vehicles are not just a mere compilation of millions of lines of code executing and exhibiting their safe operations on the road from point A to point B; it’s also about taking the interests of other human drivers sharing the road, following policies and moral values, making ethical decisions, while escaping the legal issues one may get into in the events of accidents and collisions. However, as promising technological advancements in artificially intelligent autonomous vehicles sound, effective encoding of human moral values and ethics have still not been showcased. A thorough review of extant literature and an understanding and study of a connection of human ethical and moral values with that of an autonomous vehicle has been presented in this dissertation while exploring legal implications associated with these vehicles and pre-established legal policies, bills and acts. This dissertation also provides a characterization of trust issues as they pertain to the areas of cybersecurity and intelligent autonomous systems. Additionally, an understanding and study of advanced features behind autonomous or self-driving cars which leverage wireless technology, Bluetooth, VANETs, V2V communication, Milimeter Wave radar, LiDAR, sensors, and cameras, etc. was also presented. An exploration, identification and addressing of some popular threats, vulnerabilities and hacking attacks in self-driving cars is also included along with an establishment of a relationship between these threats, trust, and reliability. An analysis of alert systems in self-driving cars is also presented.

CHAPTER 8. LIMITATIONS AND FUTURE WORK

The dataset that was augmented, labelled, classified, pre-processed, and applied towards the creation of the NoTrust ANN model was sourced from PDF versions of collision reports involving autonomous vehicles (see Appendix figures B1 through B8 for screen capture of sample PDF reports), as provided by California DMV. For the purposes of this research, only the data between October 2014 and March 2020 was taken into consideration. This dataset only consisted of 256 collision reports which was converted to 256 rows of CSV file (see Appendix figure B9 for screen capture of the CSV data file) and then augmented to 5256 rows of data. For future research, data from collision reports post March 2020 can also be included towards model generation and a combination of several other attributes of the dataset can be taken into consideration during data labelling, classification, and pre-processing. Additionally, meaningful data can also be extracted from disengagement reports provided by California DMV and used towards model generation and enhancement of this linear sequential model. In addition to enhancing this linear sequential model, several other types of models can be explored and generated using different algorithms and compilation techniques. Data analysis and visualization of the data based upon model evaluation and predictions can also be enhanced using combination of other attributes from the dataset that are not mentioned in the analysis and visualizations claimed by this research study.

Further information about the autonomous vehicle and the other vehicle involved in collision in terms of the vehicle attributes, characteristics, number of sensors and the type of sensors that the vehicle is equipped with, can be procured from the vehicle manufacturers, and utilized towards model generation. Moreover, information about the roadway conditions and the operation of the vehicle sensor mechanics on unprecedented roadway conditions in which the vehicle is being driven in, can also be gathered, and analyzed. Another enhancement can be made to this research study by exploring official autonomous vehicle datasets, as/when, provided by autonomous vehicles manufacturers or DMV from other states in the US. This research study can also be expanded and internationalized to included autonomous vehicle collision data from other countries.

APPENDIX A. SUPPLEMENTAL TABLES

Table A1: Comprehensive Data Attributes Table

Column Name	Description	Feature Type	Data Type
PDF_file_Number	Name of the PDF file (String)	Categorical	Object
Manufacturer_Name	Manufacturer of Autonomous vehicle involved in crash (String)	Categorical	Object
Business_Name	Business name of the Manufacturer (String)	Categorical	Object
Date_of_Accident	Date of accident (String)	Categorical	Object
Time_of_Accident	Time of accident (String)	Categorical	Object
Vehicle_1_Year	Year Autonomous vehicle was manufactured (String)	Categorical	Object
Vehicle_1_Make	Make of Autonomous Vehicle (String)	Categorical	Object
Vehicle_1_Model	Model of Autonomous Vehicle (String)	Categorical	Object
Vehicle_1_was	State of autonomous vehicle – Moving or Stopped in Traffic (String)	Categorical	Object
Involved_in_Vehicle_1_Accident_Pedestrian	Pedestrian involved in Autonomous vehicle crash (String)	Categorical	Object
Involved_in_Vehicle_1_Accident_Bicyclist	Bicyclist involved in Autonomous vehicle crash (String)	Categorical	Object
Involved_in_Vehicle_1_Accident_Other	Anything other than pedestrian or bicyclist involved in Autonomous vehicle crash (String)	Categorical	Object
Number_of_vehicles_involved_with_Vehicle_1	Number of vehicles involved in crash with autonomous vehicle (String)	Categorical	Object
Vehicle_Damage	Damage sustained by autonomous vehicle (String)	Categorical	Object
Damaged_Area	Autonomous vehicle damage area (String)	Categorical	Object
Vehicle_2_Year	Year other vehicle involved in crash was manufactured (String)	Categorical	Object
Vehicle_2_Make	Make of second vehicle involved in crash (String)	Categorical	Object
Vehicle_2_Model	Model of second vehicle involved in crash (String)	Categorical	Object
Vehicle_2_was	State of second vehicle involved in crash (String)	Categorical	Object
Involved_in_Vehicle_2_Accident_Pedestrian	Pedestrian involved in second vehicle crash (String)	Categorical	Object
Involved_in_Vehicle_2_Accident_Bicyclist	Bicyclist involved in second vehicle crash (String)	Categorical	Object
Involved_in_Vehicle_2_Accident_Other	Anything other than pedestrian or bicyclist involved in second vehicle crash (String)	Categorical	Object
Number_of_vehicles_involved_with_Vehicle_2	Number of vehicles involved in crash with second vehicle (String)	Categorical	Object
Injured	Any injuries (String)	Categorical	Object
Injured_Driver	Injuries sustained by Driver (String)	Categorical	Object
Injured_Passenger	Injuries sustained by Passenger (String)	Categorical	Object
Injured_Bicyclist	Injuries sustained by Bicyclist (String)	Categorical	Object
Vehicle_Driving_Mode	Driving mode of autonomous vehicle (String)	Categorical	Object
Vehicle_1_Weather_Clear	Clear weather condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Weather_Clear	Clear weather condition for second vehicle (String)	Categorical	Object
Vehicle_1_Weather_Cloudy	Cloudy weather condition for Autonomous vehicle (String)	Categorical	Object

Table A1: Comprehensive Data Attributes Table (continued)

Column Name	Description	Feature Type	Data Type
Vehicle_2_Weather_Cloudy	Cloudy weather condition for second vehicle (String)	Categorical	Object
Vehicle_1_Weather_Raining	Raining weather condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Weather_Raining	Raining weather condition for second vehicle (String)	Categorical	Object
Vehicle_1_Weather_Snowing	Snowing weather condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Weather_Snowing	Snowing weather condition for second vehicle (String)	Categorical	Object
Vehicle_1_Weather_Fog/Visibility	Fog/Visibility weather condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Weather_Fog/Visibility	Fog/Visibility weather condition for second vehicle (String)	Categorical	Object
Vehicle_1_Weather_Other	Weather condition for Autonomous vehicle other than the one already listed before (String)	Categorical	Object
Vehicle_2_Weather_Other	Weather condition for second vehicle other than the one already listed before (String)	Categorical	Object
Vehicle_1_Weather_Wind	Wind weather condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Weather_Wind	Wind weather condition for second vehicle (String)	Categorical	Object
Vehicle_1_Lighting_Daylight	Daylight lighting condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Lighting_Daylight	Daylight lighting condition for second vehicle (String)	Categorical	Object
Vehicle_1_Lighting_Dusk-Dawn	Dusk/Dawn lighting condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Lighting_Dusk-Dawn	Dusk/Dawn lighting condition for second vehicle (String)	Categorical	Object
Vehicle_1_Lighting_Dark-Street-Lights	Dark Street with Lights lighting condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Lighting_Dark-Street-Lights	Dark Street with Lights lighting condition for second vehicle (String)	Categorical	Object
Vehicle_1_Lighting_Dark-No-Street-Lights	Dark Street without Lights lighting condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Lighting_Dark-No-Street-Lights	Dark Street without Lights lighting condition for second vehicle (String)	Categorical	Object
Vehicle_1_Lighting_Dark-Street-Lights-Not-Functioning	Dark Street with non-functional Lights lighting condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Lighting_Dark-Street-Lights-Not-Functioning	Dark Street with non-functional Lights lighting condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Surface-Dry	Dry Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Roadway_Surface-Dry	Dry Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Surface-Wet	Wet Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object

Table A1: Comprehensive Data Attributes Table (continued)

Column Name	Description	Feature Type	Data Type
Vehicle_2_Roadway_Surface-Wet	Wet Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Surface-Snowy-Icy	Snowy/Icy Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Roadway_Surface-Snowy-Icy	Snowy/Icy Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Surface-Slippery-Muddy-Oily-etc	Slippery (Muddy,Oily,etc) Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Roadway_Surface-Slippery-Muddy-Oily-etc	Slippery (Muddy,Oily,etc) Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Conditions-Holes-Deep-Rut	Holes, Deep Rut Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Roadway_Conditions-Holes-Deep-Rut	Holes, Deep Rut Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Conditions-Loose-Material-on-Roadway	Loose Material on Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Roadway_Conditions-Loose-Material-on-Roadway	Loose Material on Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Conditions-Obstruction-on-Roadway	Obstruction on Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Roadway_Conditions-Obstruction-on-Roadway	Obstruction on Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Conditions-Construction-Repair-Zone	Construction on Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Roadway_Conditions-Construction-Repair-Zone	Construction on Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Conditions-Reduced-Roadway-Width	Reduced Width on Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Roadway_Conditions-Reduced-Roadway-Width	Reduced Width on Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Conditions-Flooded	Flooded Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Roadway_Conditions-Flooded	Flooded Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Roadway_Conditions-Other	Roadway Surface condition for Autonomous vehicle other than the one already listed before (String)	Categorical	Object
Vehicle_2_Roadway_Conditions-Other	Roadway Surface condition for second vehicle other than the one already listed before (String)	Categorical	Object

Table A1: Comprehensive Data Attributes Table (continued)

Column Name	Description	Feature Type	Data Type
Vehicle_1_Roadway_Conditions-No-Unusual-Conditions	No Unusual Roadway Surface condition for Autonomous vehicle (String)	Categorical	Object
Vehicle_2_Roadway_Conditions-No-Unusual-Conditions	No Unusual Roadway Surface condition for second vehicle (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Stopped	Vehicle Movement of Autonomous vehicle Preceding Collision - Stopped (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Stopped	Vehicle Movement for second vehicle Preceding Collision - Stopped (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Proceeding-Straight	Vehicle Movement of Autonomous vehicle Preceding Collision – Proceeding Straight (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Proceeding-Straight	Vehicle Movement for second vehicle Preceding Collision – Proceeding Straight (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Ran-Off-Road	Vehicle Movement of Autonomous vehicle Preceding Collision – Ran Off Road (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Ran-Off-Road	Vehicle Movement for second vehicle Preceding Collision – Ran Off Road (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Making-Right-Turn	Vehicle Movement of Autonomous vehicle Preceding Collision – Making Right Turn (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Making-Right-Turn	Vehicle Movement for second vehicle Preceding Collision – Making Right Turn (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Making-Left-Turn	Vehicle Movement of Autonomous vehicle Preceding Collision – Making Left Turn (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Making-Left-Turn	Vehicle Movement for second vehicle Preceding Collision – Making Left Turn (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Making-U-Turn	Vehicle Movement of Autonomous vehicle Preceding Collision – Making U Turn (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Making-U-Turn	Vehicle Movement for second vehicle Preceding Collision – Making U Turn (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Backing	Vehicle Movement of Autonomous vehicle Preceding Collision – Backing (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Backing	Vehicle Movement for second vehicle Preceding Collision – Backing (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Slowing/Stopping	Vehicle Movement of Autonomous vehicle Preceding Collision – Slowing/Stopping (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Slowing/Stopping	Vehicle Movement for second vehicle Preceding Collision – Slowing/Stopping (String)	Categorical	Object

Table A1: Comprehensive Data Attributes Table (continued)

Column Name	Description	Feature Type	Data Type
Vehicle_1_Movement_Preceding_Collision-Passing-Other-Vehicle	Vehicle Movement of Autonomous vehicle Preceding Collision – Passing Other Vehicle (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Passing-Other-Vehicle	Vehicle Movement for second vehicle Preceding Collision – Passing Other Vehicle (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Changing-Lanes	Vehicle Movement of Autonomous vehicle Preceding Collision – Changing Lanes (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Changing-Lanes	Vehicle Movement for second vehicle Preceding Collision – Changing Lanes (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Parking-Manuever	Vehicle Movement of Autonomous vehicle Preceding Collision – Parking Manuever (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Parking-Manuever	Vehicle Movement for second vehicle Preceding Collision – Parking Manuever (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Entering-Traffic	Vehicle Movement of Autonomous vehicle Preceding Collision – Entering Traffic (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Entering-Traffic	Vehicle Movement for second vehicle Preceding Collision – Entering Traffic (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Other-Unsafe-Turning	Vehicle Movement of Autonomous vehicle Preceding Collision – Other Unsafe Turning (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Other-Unsafe-Turning	Vehicle Movement for second vehicle Preceding Collision – Other Unsafe Turning (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Xing-Into-Opposing-Lane	Vehicle Movement of Autonomous vehicle Preceding Collision – Crossing into Opposing Lane (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Xing-Into-Opposing-Lane	Vehicle Movement for second vehicle Preceding Collision – Crossing into Opposing Lane (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Parked	Vehicle Movement of Autonomous vehicle Preceding Collision – Parked (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Parked	Vehicle Movement for second vehicle Preceding Collision – Parked (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Merging	Vehicle Movement of Autonomous vehicle Preceding Collision – Merging (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Merging	Vehicle Movement for second vehicle Preceding Collision – Merging (String)	Categorical	Object
Vehicle_1_Movement_Preceding_Collision-Travelling-Wrong-Way	Vehicle Movement of Autonomous vehicle Preceding Collision – Travelling Wrong Way (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Travelling-Wrong-Way	Vehicle Movement for second vehicle Preceding Collision – Travelling Wrong Way (String)	Categorical	Object

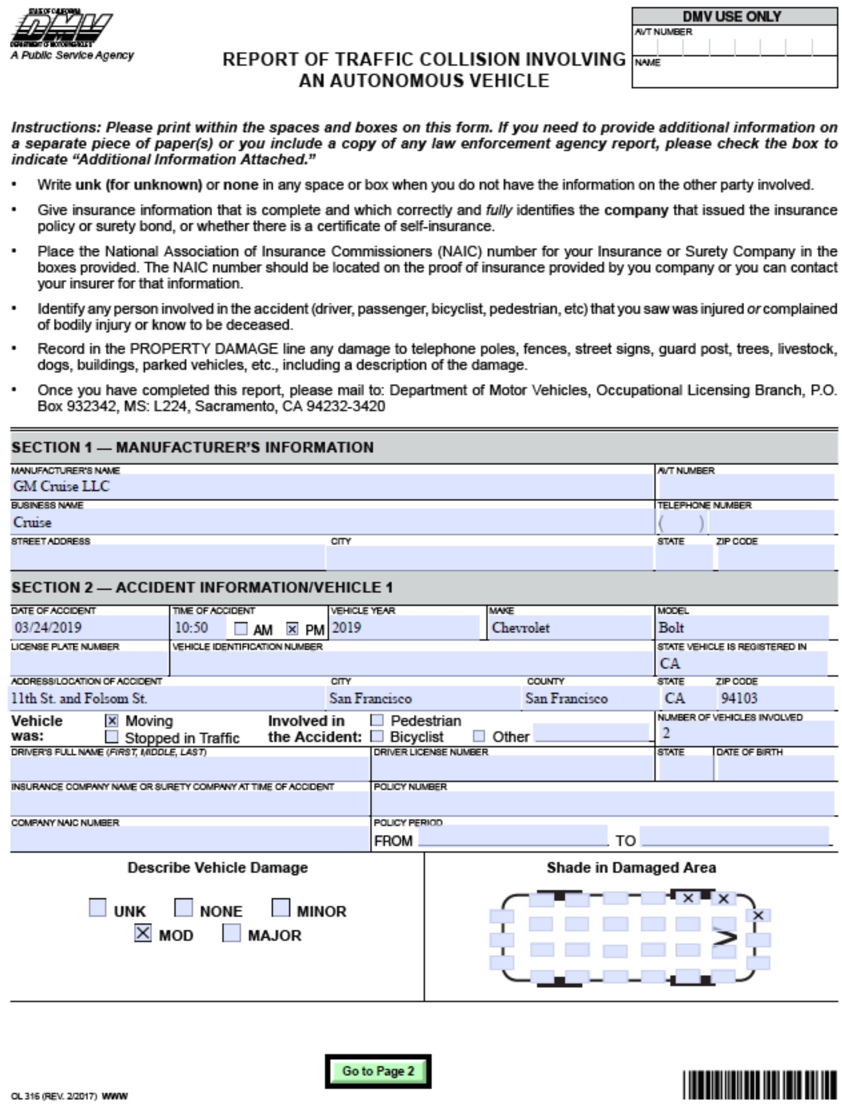
Table A1: Comprehensive Data Attributes Table (continued)

Column Name	Description	Feature Type	Data Type
Vehicle_1_Movement_Preceding_Collision-Other	Vehicle Movement of Autonomous vehicle Preceding Collision other than the one list before (String)	Categorical	Object
Vehicle_2_Movement_Preceding_Collision-Other	Vehicle Movement for second vehicle Preceding Collision other than the one listed before (String)	Categorical	Object
Vehicle_1_Type_of_Collision-Head-On	Type of Collision that Autonomous vehicle was involved in was – Head On (String)	Categorical	Object
Vehicle_2_Type_of_Collision-Head-On	Type of Collision that second vehicle was involved in was - Head On (String)	Categorical	Object
Vehicle_1_Type_of_Collision-Side-Swipe	Type of Collision that Autonomous vehicle was involved in was – Side Swipe (String)	Categorical	Object
Vehicle_2_Type_of_Collision-Side-Swipe	Type of Collision that second vehicle was involved in was – Side Swipe (String)	Categorical	Object
Vehicle_1_Type_of_Collision-Rear-End	Type of Collision that Autonomous vehicle was involved in was – Rear End (String)	Categorical	Object
Vehicle_2_Type_of_Collision-Rear-End	Type of Collision that second vehicle was involved in was – Rear End (String)	Categorical	Object
Vehicle_1_Type_of_Collision-Broadside	Type of Collision that Autonomous vehicle was involved in was – Broadside (String)	Categorical	Object
Vehicle_2_Type_of_Collision-Broadside	Type of Collision that second vehicle was involved in was - Broadside (String)	Categorical	Object
Vehicle_1_Type_of_Collision-Hit-Object	Type of Collision that Autonomous vehicle was involved in was – Hit Object (String)	Categorical	Object
Vehicle_2_Type_of_Collision-Hit-Object	Type of Collision that second vehicle was involved in was – Hit Object (String)	Categorical	Object
Vehicle_1_Type_of_Collision-Overturned	Type of Collision that Autonomous vehicle was involved in was – Overturned (String)	Categorical	Object
Vehicle_2_Type_of_Collision-Overturned	Type of Collision that second vehicle was involved in was - Overturned (String)	Categorical	Object
Vehicle_1_Type_of_Collision-Vehicle/Pedestrian	Type of Collision that Autonomous vehicle was involved in was – Vehicle/Pedestrian (String)	Categorical	Object
Vehicle_2_Type_of_Collision-Vehicle/Pedestrian	Type of Collision that second vehicle was involved in was – Vehicle/Pedestrian (String)	Categorical	Object
Vehicle_1_Type_of_Collision-Other	Type of Collision that Autonomous vehicle was involved in was other than the one listed before (String)	Categorical	Object
Vehicle_2_Type_of_Collision-Other	Type of Collision that second vehicle was involved in was other than the one listed before (String)	Categorical	Object
CVC_Sections_Violated_Cited	Other Associated Factors – Was there any citation for CVC Section Violation (String)	Categorical	Object
Vision_Obscurement	Other Associated Factors – Vision Obscurement (String)	Categorical	Object
Inattention	Other Associated Factors – Inattention (String)	Categorical	Object
Stop_and_Go_Traffic	Other Associated Factors – Stop and Go Traffic (String)	Categorical	Object
Entering/Leaving_Ramp	Other Associated Factors – Was the vehicle entering or leaving ramp (String)	Categorical	Object
Previous_Collision	Other Associated Factors – Was there any previous collision (String)	Categorical	Object

Table A1: Comprehensive Data Attributes Table (continued)

Column Name	Description	Feature Type	Data Type
Unfamiliar_With_Road	Other Associated Factors – was the vehicle unfamiliar with road (String)	Categorical	Object
Defective_WEH_Equip_Cited	Other Associated Factors – Was there any citation for Defective WEH Equipment (String)	Categorical	Object
Uninvolved_Vehicle	Other Associated Factors – Uninvolved Vehicle (String)	Categorical	Object
Other	Other Associated Factors other than the one listed before (String)	Categorical	Object
None_Apparent	Other Associated Factors – None Apparent (String)	Categorical	Object
Runaway_Vehicle	Other Associated Factors – Runaway Vehicle (String)	Categorical	Object

APPENDIX B. SUPPLEMENTAL FIGURES



A Public Service Agency

DMV USE ONLY

A/T NUMBER

NAME

REPORT OF TRAFFIC COLLISION INVOLVING AN AUTONOMOUS VEHICLE

Instructions: Please print within the spaces and boxes on this form. If you need to provide additional information on a separate piece of paper(s) or you include a copy of any law enforcement agency report, please check the box to indicate "Additional Information Attached."

- Write **unk (for unknown)** or **none** in any space or box when you do not have the information on the other party involved.
- Give insurance information that is complete and which correctly and *fully* identifies the **company** that issued the insurance policy or surety bond, or whether there is a certificate of self-insurance.
- Place the National Association of Insurance Commissioners (NAIC) number for your Insurance or Surety Company in the boxes provided. The NAIC number should be located on the proof of insurance provided by you company or you can contact your insurer for that information.
- Identify any person involved in the accident (driver, passenger, bicyclist, pedestrian, etc) that you saw was injured *or* complained of bodily injury or know to be deceased.
- Record in the PROPERTY DAMAGE line any damage to telephone poles, fences, street signs, guard post, trees, livestock, dogs, buildings, parked vehicles, etc., including a description of the damage.
- Once you have completed this report, please mail to: Department of Motor Vehicles, Occupational Licensing Branch, P.O. Box 932342, MS: L224, Sacramento, CA 94232-3420

SECTION 1 — MANUFACTURER'S INFORMATION

MANUFACTURER'S NAME: GM Cruise LLC | A/T NUMBER:
BUSINESS NAME: Cruise | TELEPHONE NUMBER: ( )
STREET ADDRESS: | CITY: | STATE: | ZIP CODE:

SECTION 2 — ACCIDENT INFORMATION/VEHICLE 1

DATE OF ACCIDENT: 03/24/2019 | TIME OF ACCIDENT: 10:50 ☐ AM ☒ PM | VEHICLE YEAR: 2019 | MAKE: Chevrolet | MODEL: Bolt
LICENSE PLATE NUMBER: | VEHICLE IDENTIFICATION NUMBER: | STATE VEHICLE IS REGISTERED IN: CA
ADDRESS/LOCATION OF ACCIDENT: 11th St. and Folsom St. | CITY: San Francisco | COUNTY: San Francisco | STATE: CA | ZIP CODE: 94103

Vehicle was: ☒ Moving ☐ Stopped in Traffic | **Involved in the Accident:** ☐ Pedestrian ☐ Bicyclist ☐ Other | NUMBER OF VEHICLES INVOLVED: 2

DRIVER'S FULL NAME (FIRST, MIDDLE, LAST): | DRIVER LICENSE NUMBER: | STATE: | DATE OF BIRTH:
INSURANCE COMPANY NAME OR SURETY COMPANY AT TIME OF ACCIDENT: | POLICY NUMBER:
COMPANY NAIC NUMBER: | POLICY PERIOD FROM ___ TO ___

Describe Vehicle Damage

☐ UNK ☐ NONE ☐ MINOR
☒ MOD ☐ MAJOR

Shade in Damaged Area

Go to Page 2

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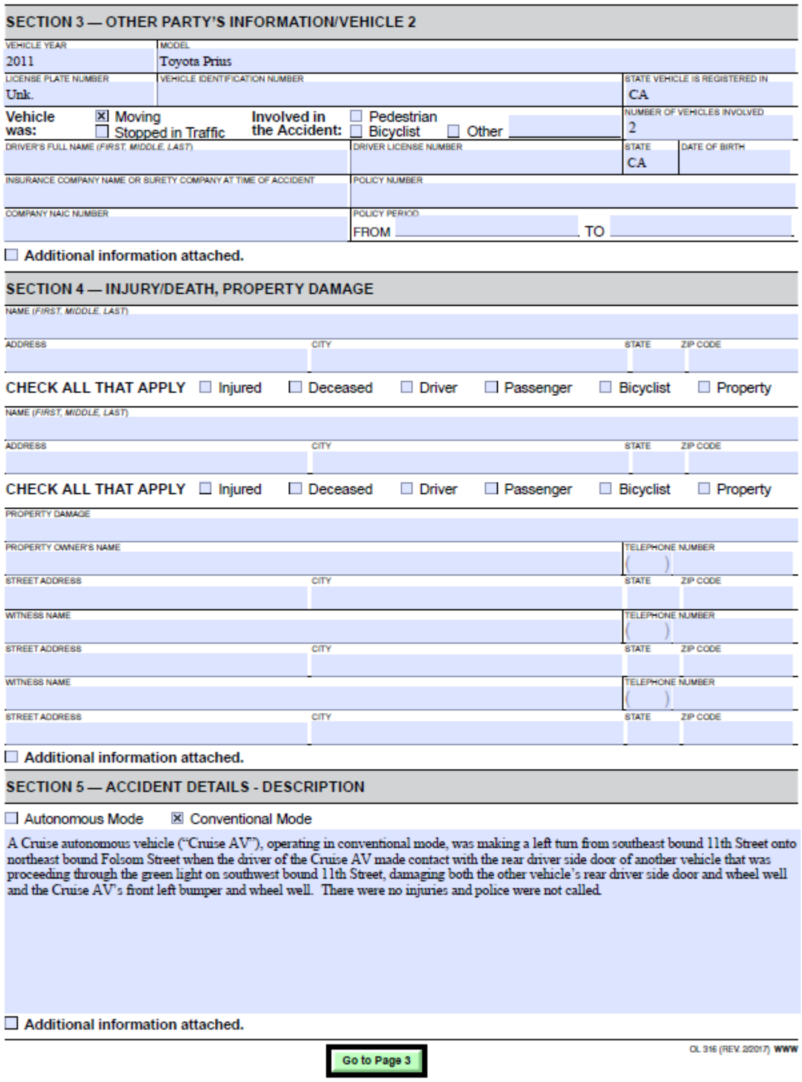
Figure B1: Screen Capture of Sample PDF Report Page 1



SECTION 3 — OTHER PARTY'S INFORMATION/VEHICLE 2

VEHICLE YEAR: 2011
MODEL: Toyota Prius
LICENSE PLATE NUMBER: Unk.
VEHICLE IDENTIFICATION NUMBER:
STATE VEHICLE IS REGISTERED IN: CA
Vehicle was: ☒ Moving ☐ Stopped in Traffic
Involved in the Accident: ☐ Pedestrian ☐ Bicyclist ☐ Other
NUMBER OF VEHICLES INVOLVED: 2
DRIVER'S FULL NAME (FIRST, MIDDLE, LAST)
DRIVER LICENSE NUMBER
STATE: CA
DATE OF BIRTH
INSURANCE COMPANY NAME OR SURETY COMPANY AT TIME OF ACCIDENT
POLICY NUMBER
COMPANY NAIC NUMBER
POLICY PERIOD FROM ____ TO ____

☐ Additional information attached.

SECTION 4 — INJURY/DEATH, PROPERTY DAMAGE

NAME (FIRST, MIDDLE, LAST)
ADDRESS | CITY | STATE | ZIP CODE
CHECK ALL THAT APPLY ☐ Injured ☐ Deceased ☐ Driver ☐ Passenger ☐ Bicyclist ☐ Property
NAME (FIRST, MIDDLE, LAST)
ADDRESS | CITY | STATE | ZIP CODE
CHECK ALL THAT APPLY ☐ Injured ☐ Deceased ☐ Driver ☐ Passenger ☐ Bicyclist ☐ Property
PROPERTY DAMAGE
PROPERTY OWNER'S NAME | TELEPHONE NUMBER ( )
STREET ADDRESS | CITY | STATE | ZIP CODE
WITNESS NAME | TELEPHONE NUMBER ( )
STREET ADDRESS | CITY | STATE | ZIP CODE
WITNESS NAME | TELEPHONE NUMBER ( )
STREET ADDRESS | CITY | STATE | ZIP CODE

☐ Additional information attached.

SECTION 5 — ACCIDENT DETAILS - DESCRIPTION

☐ Autonomous Mode ☒ Conventional Mode

A Cruise autonomous vehicle ("Cruise AV"), operating in conventional mode, was making a left turn from southeast bound 11th Street onto northeast bound Folsom Street when the driver of the Cruise AV made contact with the rear driver side door of another vehicle that was proceeding through the green light on southwest bound 11th Street, damaging both the other vehicle's rear driver side door and wheel well and the Cruise AV's front left bumper and wheel well. There were no injuries and police were not called.

☐ Additional information attached.

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Figure B2: Screen Capture of Sample PDF Report Page 2

ITEMS MARKED BELOW FOLLOWED BY AN ASTERISK (*) SHOULD BE EXPLAINED IN THE NARRATIVE

WEATHER (MARK 1 to 2 ITEMS)	VEH 1	VEH 2	MOVEMENT PRECEDING COLLISION	VEH 1	VEH 2	OTHER ASSOCIATED FACTOR(s) (MARK ALL APPLICABLE)
A. CLEAR	X	X	A. STOPPED			A. CVC SECTIONS VIOLATED
B. CLOUDY			B. PROCEEDING STRAIGHT		X	CITED ☐ YES ☐ NO
C. RAINING			C. RAN OFF ROAD			
D. SNOWING			D. MAKING RIGHT TURN			
E. FOG/VISIBILITY			E. MAKING LEFT TURN	X		
F. OTHER			F. MAKING U TURN			B. VISION OBSCUREMENT ☐
G. WIND			G. BACKING			C. INATTENTION* ☐
LIGHTING			H. SLOWING/STOPPING			D. STOP & GO TRAFFIC ☐
A. DAYLIGHT			I. PASSING OTHER VEHICLE			E. ENTERING/LEAVING RAMP ☐
B. DUSK – DAWN			J. CHANGING LANES			F. PREVIOUS COLLISION ☐
C. DARK –STREET LIGHTS	X	X	K. PARKING MANUEVER			G. UNFAMILIAR WITH ROAD ☐
D. DARK – NO STREET LIGHTS			L. ENTERING TRAFFIC			H. DEFECTIVE WEH EQUIP
E. DARK –STREET LIGHTS NOT FUNCTIONING*			M. OTHER UNSAFE TURNING			CITED ☐ YES ☐ NO
ROADWAY SURFACE			N. XING INTO OPPOSING LANE			
A. DRY	X	X	O. PARKED			I. UNINVOLVED VEHICLE ☐
B. WET			P. MERGING			J. OTHER* ☐
C. SNOWY – ICY			Q. TRAVELING WRONG WAY			K. NONE APPARENT ☐
D. SLIPPERY (MUDDY, OILY, ETC.)			R. OTHER*			L. RUNAWAY VEHICLE ☐
ROADWAY CONDITIONS (MARK 1 TO 2 ITEMS)			**TYPE OF COLLISION**			
A. HOLES, DEEP RUT*			A. HEAD-ON			
B. LOOSE MATERIAL ON ROADWAY			B. SIDE SWIPE		X	
C. OBSTRUCTION ON ROADWAY*			C. REAR END			
D. CONSTRUCTION – REPAIR ZONE			D. BROADSIDE			
E. REDUCED ROADWAY WIDTH			E. HIT OBJECT			
F. FLOODED*			F. OVERTURNED			
G. OTHER*			G. VEHICLE/PEDESTRIAN			
H. NO UNUSUAL CONDITIONS	X	X	H. OTHER*			

SECTION 6 — CERTIFICATION

I certify (or declare) under penalty of perjury under the laws of the State of California that the foregoing is true and correct.

I further certify that I am the authorized Administrator of the program for the above named employer.

PROGRAM DIRECTOR/AUTHORIZED REPRESENTATIVE PRINTED NAME AND TITLE	TELEPHONE NUMBER
Kevin Chu, Director of AV Engineering	( )
SIGNATURE X	DATE SIGNED 04/01/2019

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Print | Clear Form

Figure B3: Screen Capture of Sample PDF Report Page 3

DMV
A Public Service Agency

DMV USE ONLY
AVT NUMBER
NAME

REPORT OF TRAFFIC COLLISION INVOLVING AN AUTONOMOUS VEHICLE

Instructions: Please print within the spaces and boxes on this form. If you need to provide additional information on a separate piece of paper(s) or you include a copy of any law enforcement agency report, please check the box to indicate "Additional Information Attached."

- Write **unk (for unknown)** or **none** in any space or box when you do not have the information on the other party involved.
- Give insurance information that is complete and which correctly and *fully* identifies the **company** that issued the insurance policy or surety bond, or whether there is a certificate of self-insurance.
- Place the National Association of Insurance Commissioners (NAIC) number for your Insurance or Surety Company in the boxes provided. The NAIC number should be located on the proof of insurance provided by you company or you can contact your insurer for that information.
- Identify any person involved in the accident (driver, passenger, bicyclist, pedestrian, etc) that you saw was injured or complained of bodily injury or know to be deceased.
- Record in the PROPERTY DAMAGE line any damage to telephone poles, fences, street signs, guard post, trees, livestock, dogs, buildings, parked vehicles, etc., including a description of the damage.
- Once you have completed this report, please mail to: Department of Motor Vehicles, Occupational Licensing Branch, P.O. Box 932342, MS: L224, Sacramento, CA 94232-3420

SECTION 1 — MANUFACTURER'S INFORMATION

MANUFACTURER'S NAME: Toyota Research Institute, Inc.	AVT NUMBER
BUSINESS NAME: Toyota Research Institute	TELEPHONE NUMBER: ( )
STREET ADDRESS / CITY	STATE / ZIP CODE

SECTION 2 — ACCIDENT INFORMATION/VEHICLE 1

DATE OF ACCIDENT: 08/07/2018	TIME OF ACCIDENT: 11:50 ☑ AM ☐ PM	VEHICLE YEAR: 2016	MAKE: Lexus	MODEL: LX 600H L
LICENSE PLATE NUMBER	VEHICLE IDENTIFICATION NUMBER			STATE VEHICLE IS REGISTERED IN
ADDRESS/LOCATION OF ACCIDENT: I-80 East		CITY: Crockett	COUNTY: Contra Costa	STATE: CA ZIP CODE: 94525

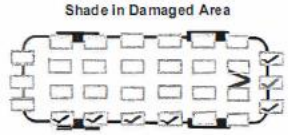
Vehicle was: ☑ Moving ☐ Stopped in Traffic
Involved in the Accident: ☐ Pedestrian ☐ Bicyclist ☐ Other
NUMBER OF VEHICLES INVOLVED: 3

DRIVER'S FULL NAME (FIRST, MIDDLE, LAST)	DRIVER LICENSE NUMBER	STATE	DATE OF BIRTH
INSURANCE COMPANY NAME OR SURETY COMPANY AT TIME OF ACCIDENT	POLICY NUMBER		
COMPANY NAIC NUMBER	POLICY PERIOD FROM ____ TO ____		

Describe Vehicle Damage

☐ UNK ☐ NONE ☐ MINOR
☐ MOD ☑ MAJOR

Shade In Damaged Area



OL 316 (REV. 2/2017) WWW

Figure B4: Screen Capture of Sample Scanned PDF Report Page 1

SECTION 3 — OTHER PARTY'S INFORMATION/VEHICLE 2

VEHICLE YEAR: 2005
MODEL: Prius

LICENSE PLATE NUMBER | VEHICLE IDENTIFICATION NUMBER | STATE VEHICLE IS REGISTERED IN

Vehicle was: ☑ Moving ☐ Stopped in Traffic

Involved in the Accident: ☐ Pedestrian ☐ Bicyclist ☐ Other

NUMBER OF VEHICLES INVOLVED: 3

DRIVER'S FULL NAME (FIRST, MIDDLE, LAST) | DRIVER LICENSE NUMBER | STATE | DATE OF BIRTH

INSURANCE COMPANY NAME OR SURETY COMPANY AT TIME OF ACCIDENT | POLICY NUMBER

COMPANY NAIC NUMBER | POLICY PERIOD FROM ____ TO ____

☐ **Additional information attached.**

SECTION 4 — INJURY/DEATH, PROPERTY DAMAGE

NAME (FIRST, MIDDLE, LAST)

ADDRESS | CITY | STATE | ZIP CODE

CHECK ALL THAT APPLY ☐ Injured ☐ Deceased ☐ Driver ☐ Passenger ☐ Bicyclist ☐ Property

NAME (FIRST, MIDDLE, LAST)

ADDRESS | CITY | STATE | ZIP CODE

CHECK ALL THAT APPLY ☐ Injured ☐ Deceased ☐ Driver ☐ Passenger ☐ Bicyclist ☐ Property

PROPERTY DAMAGE

PROPERTY OWNER'S NAME | TELEPHONE NUMBER ( )

STREET ADDRESS | CITY | STATE | ZIP CODE

WITNESS NAME | TELEPHONE NUMBER ( )

STREET ADDRESS | CITY | STATE | ZIP CODE

WITNESS NAME | TELEPHONE NUMBER ( )

STREET ADDRESS | CITY | STATE | ZIP CODE

☐ **Additional information attached.**

SECTION 5 — ACCIDENT DETAILS - DESCRIPTION

☐ Autonomous Mode ☑ Conventional Mode

A Toyota Research Institute Vehicle (the "TRI Vehicle") was travelling under manual control in the #1 lane on I-80 Eastbound near the Pomona Street exit in Crockett. A Hyundai attempted to change from the #3 lane to the #2 lane. The Hyundai impacted a Prius that was already in the #2 lane, which caused the Prius to enter the #1 lane, where it impacted the TRI Vehicle. The TRI Vehicle then impacted the center barrier and came to a stop in the roadway. The Hyundai stopped on the right shoulder, and the Prius eventually came to rest along the dirt embankment

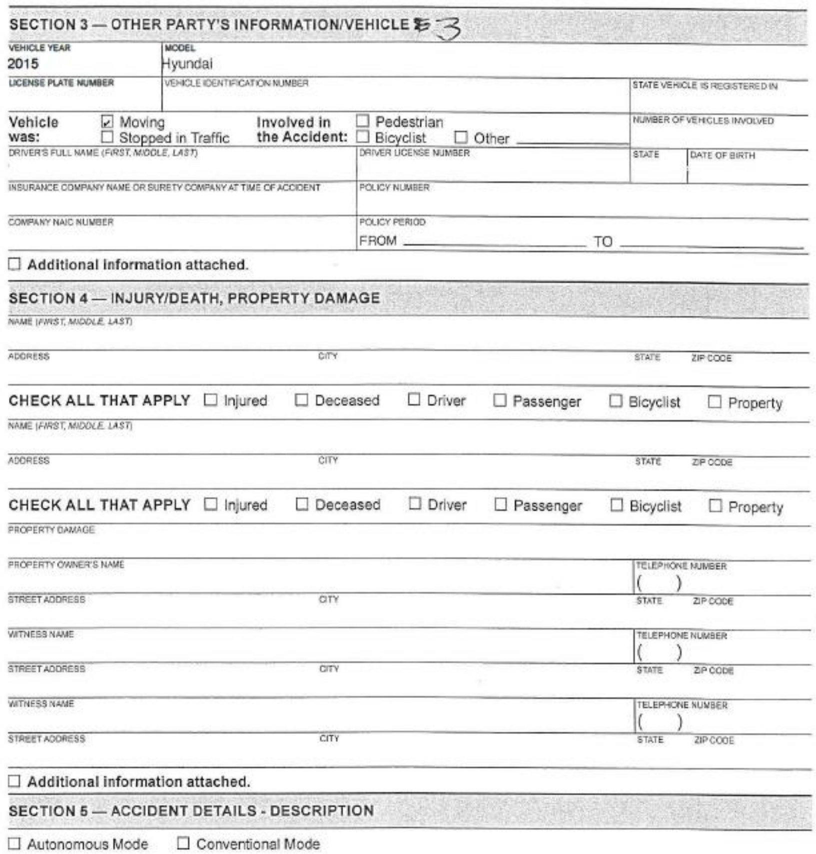
The California Highway Patrol responded to the scene, and the vehicles were cleared off the roadway.

ATTACHED: Additional information relating the Hyundai vehicle and driver.

☑ **Additional information attached.**

OL 316 (REV. 2/2017) WWW

Figure B5: Screen Capture of Sample Scanned PDF Report Page 2



SECTION 3 — OTHER PARTY'S INFORMATION/VEHICLE 3

VEHICLE YEAR: 2015
MODEL: Hyundai
LICENSE PLATE NUMBER
VEHICLE IDENTIFICATION NUMBER
STATE VEHICLE IS REGISTERED IN

Vehicle was: ☑ Moving ☐ Stopped in Traffic
Involved in the Accident: ☐ Pedestrian ☐ Bicyclist ☐ Other
NUMBER OF VEHICLES INVOLVED

DRIVER'S FULL NAME (FIRST, MIDDLE, LAST)
DRIVER LICENSE NUMBER
STATE
DATE OF BIRTH

INSURANCE COMPANY NAME OR SURETY COMPANY AT TIME OF ACCIDENT
POLICY NUMBER

COMPANY NAIC NUMBER
POLICY PERIOD
FROM ______ TO ______

☐ Additional information attached.

SECTION 4 — INJURY/DEATH, PROPERTY DAMAGE

NAME (FIRST, MIDDLE, LAST)
ADDRESS
CITY
STATE
ZIP CODE

CHECK ALL THAT APPLY ☐ Injured ☐ Deceased ☐ Driver ☐ Passenger ☐ Bicyclist ☐ Property

NAME (FIRST, MIDDLE, LAST)
ADDRESS
CITY
STATE
ZIP CODE

CHECK ALL THAT APPLY ☐ Injured ☐ Deceased ☐ Driver ☐ Passenger ☐ Bicyclist ☐ Property

PROPERTY DAMAGE

PROPERTY OWNER'S NAME
TELEPHONE NUMBER
( )
STREET ADDRESS
CITY
STATE
ZIP CODE

WITNESS NAME
TELEPHONE NUMBER
( )
STREET ADDRESS
CITY
STATE
ZIP CODE

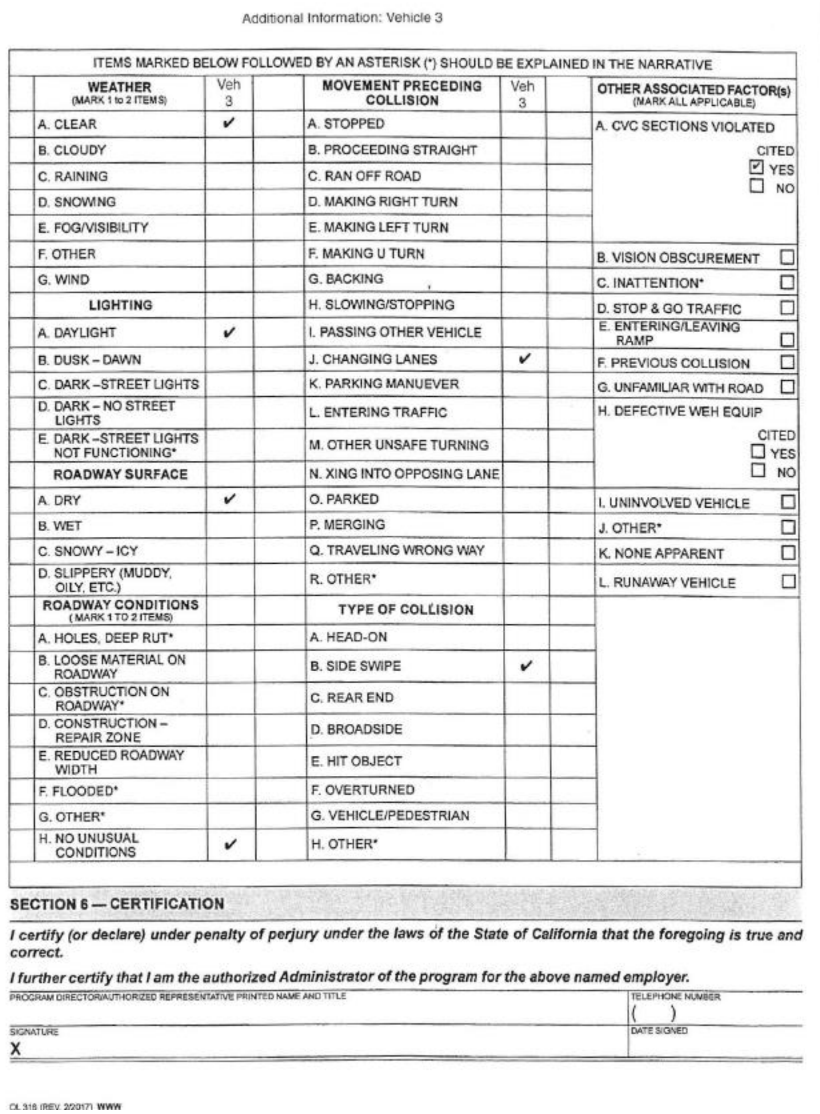
WITNESS NAME
TELEPHONE NUMBER
( )
STREET ADDRESS
CITY
STATE
ZIP CODE

☐ Additional information attached.

SECTION 5 — ACCIDENT DETAILS - DESCRIPTION

☐ Autonomous Mode ☐ Conventional Mode

Figure B6: Screen Capture of Sample Scanned PDF Report Page 3



Additional Information: Vehicle 3

ITEMS MARKED BELOW FOLLOWED BY AN ASTERISK (*) SHOULD BE EXPLAINED IN THE NARRATIVE

WEATHER (MARK 1 to 2 ITEMS)	Veh 3	MOVEMENT PRECEDING COLLISION	Veh 3	OTHER ASSOCIATED FACTOR(s) (MARK ALL APPLICABLE)
A. CLEAR	✓	A. STOPPED		A. CVC SECTIONS VIOLATED
B. CLOUDY		B. PROCEEDING STRAIGHT		CITED
C. RAINING		C. RAN OFF ROAD		☑ YES ☐ NO
D. SNOWING		D. MAKING RIGHT TURN		
E. FOG/VISIBILITY		E. MAKING LEFT TURN		
F. OTHER		F. MAKING U TURN		B. VISION OBSCUREMENT ☐
G. WIND		G. BACKING		C. INATTENTION* ☐
LIGHTING		H. SLOWING/STOPPING		D. STOP & GO TRAFFIC ☐
A. DAYLIGHT	✓	I. PASSING OTHER VEHICLE		E. ENTERING/LEAVING RAMP ☐
B. DUSK – DAWN		J. CHANGING LANES	✓	F. PREVIOUS COLLISION ☐
C. DARK –STREET LIGHTS		K. PARKING MANUEVER		G. UNFAMILIAR WITH ROAD ☐
D. DARK – NO STREET LIGHTS		L. ENTERING TRAFFIC		H. DEFECTIVE WEH EQUIP
E. DARK –STREET LIGHTS NOT FUNCTIONING*		M. OTHER UNSAFE TURNING		CITED ☐ YES
ROADWAY SURFACE		N. XING INTO OPPOSING LANE		☐ NO
A. DRY	✓	O. PARKED		I. UNINVOLVED VEHICLE ☐
B. WET		P. MERGING		J. OTHER* ☐
C. SNOWY – ICY		Q. TRAVELING WRONG WAY		K. NONE APPARENT ☐
D. SLIPPERY (MUDDY, OILY, ETC.)		R. OTHER*		L. RUNAWAY VEHICLE ☐
ROADWAY CONDITIONS (MARK 1 TO 2 ITEMS)		**TYPE OF COLLISION**		
A. HOLES, DEEP RUT*		A. HEAD-ON		
B. LOOSE MATERIAL ON ROADWAY		B. SIDE SWIPE	✓	
C. OBSTRUCTION ON ROADWAY*		C. REAR END		
D. CONSTRUCTION – REPAIR ZONE		D. BROADSIDE		
E. REDUCED ROADWAY WIDTH		E. HIT OBJECT		
F. FLOODED*		F. OVERTURNED		
G. OTHER*		G. VEHICLE/PEDESTRIAN		
H. NO UNUSUAL CONDITIONS	✓	H. OTHER*		

SECTION 6 — CERTIFICATION

I certify (or declare) under penalty of perjury under the laws of the State of California that the foregoing is true and correct.

I further certify that I am the authorized Administrator of the program for the above named employer.

PROGRAM DIRECTOR/AUTHORIZED REPRESENTATIVE PRINTED NAME AND TITLE | TELEPHONE NUMBER ( )

SIGNATURE X | DATE SIGNED

CL 316 (REV. 2/2017) WWW

Figure B7: Screen Capture of Sample Scanned PDF Report Page 4

ITEMS MARKED BELOW FOLLOWED BY AN ASTERISK (*) SHOULD BE EXPLAINED IN THE NARRATIVE

WEATHER (MARK 1 to 2 ITEMS)	VEH 1	VEH 2	MOVEMENT PRECEDING COLLISION	VEH 1	VEH 2	OTHER ASSOCIATED FACTOR(s) (MARK ALL APPLICABLE)
A. CLEAR	✓	✓	A. STOPPED			A. CVC SECTIONS VIOLATED
B. CLOUDY			B. PROCEEDING STRAIGHT	✓	✓	CITED ☐ YES ☐ NO
C. RAINING			C. RAN OFF ROAD			
D. SNOWING			D. MAKING RIGHT TURN			
E. FOG/VISIBILITY			E. MAKING LEFT TURN			
F. OTHER			F. MAKING U TURN			B. VISION OBSCUREMENT ☐
G. WIND			G. BACKING			C. INATTENTION* ☐
LIGHTING			H. SLOWING/STOPPING			D. STOP & GO TRAFFIC ☐
A. DAYLIGHT	✓	✓	I. PASSING OTHER VEHICLE			E. ENTERING/LEAVING RAMP ☐
B. DUSK – DAWN			J. CHANGING LANES			F. PREVIOUS COLLISION ☐
C. DARK – STREET LIGHTS			K. PARKING MANUEVER			G. UNFAMILIAR WITH ROAD ☐
D. DARK – NO STREET LIGHTS			L. ENTERING TRAFFIC			H. DEFECTIVE WEH EQUIP
E. DARK – STREET LIGHTS NOT FUNCTIONING*			M. OTHER UNSAFE TURNING			CITED ☐ YES
ROADWAY SURFACE			N. XING INTO OPPOSING LANE			☐ NO
A. DRY	✓	✓	O. PARKED			I. UNINVOLVED VEHICLE ☐
B. WET			P. MERGING			J. OTHER* ☐
C. SNOWY – ICY			Q. TRAVELING WRONG WAY			K. NONE APPARENT ☐
D. SLIPPERY (MUDDY, OILY, ETC.)			R. OTHER*			L. RUNAWAY VEHICLE ☐
ROADWAY CONDITIONS (MARK 1 TO 2 ITEMS)			TYPE OF COLLISION			
A. HOLES, DEEP RUT*			A. HEAD-ON			
B. LOOSE MATERIAL ON ROADWAY			B. SIDE SWIPE		✓	
C. OBSTRUCTION ON ROADWAY*			C. REAR END			
D. CONSTRUCTION – REPAIR ZONE			D. BROADSIDE			
E. REDUCED ROADWAY WIDTH			E. HIT OBJECT	✓		
F. FLOODED*			F. OVERTURNED			
G. OTHER*			G. VEHICLE/PEDESTRIAN			
H. NO UNUSUAL CONDITIONS	✓	✓	H. OTHER*			

SECTION 6 — CERTIFICATION

I certify (or declare) under penalty of perjury under the laws of the State of California that the foregoing is true and correct.

I further certify that I am the authorized Administrator of the program for the above named employer.

PROGRAM DIRECTOR/AUTHORIZED REPRESENTATIVE PRINTED NAME AND TITLE: Kelly Kay Executive Vice President

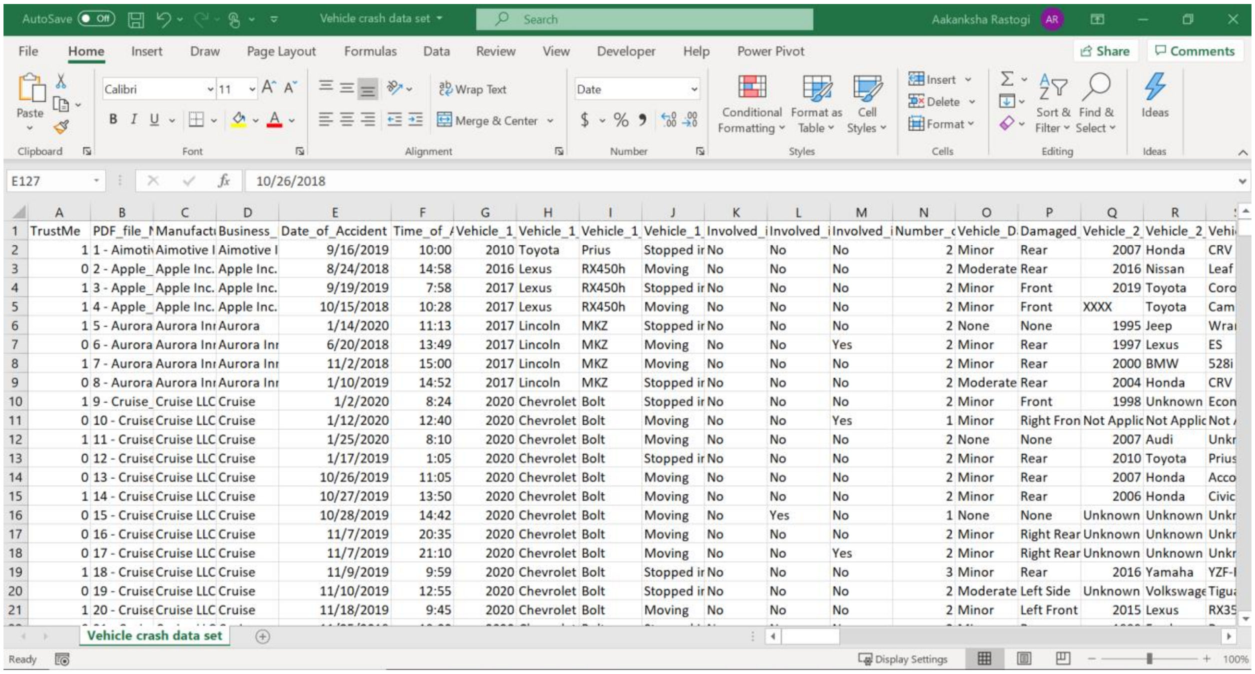
TELEPHONE NUMBER: ( )

SIGNATURE: X

DATE SIGNED: 8-16-2018

DL 316 (REV. 2/2017) WWW

Figure B8: Screen Capture of Sample Scanned PDF Report Page 5



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	TrustMe	PDF_file_N	Manufactu	Business_	Date_of_Accident	Time_of_A	Vehicle_1_	Vehicle_1_	Vehicle_1_	Vehicle_1_	Involved_i	Involved_i	Involved_i	Number_c	Vehicle_D	Damaged_	Vehicle_2_	Vehicle_2_	Vehi
2	1	1 - Aimoti	Aimotive I	Aimotive I	9/16/2019	10:00	2010	Toyota	Prius	Stopped ir	No	No	No	2	Minor	Rear	2007	Honda	CRV
3	0	2 - Apple_	Apple Inc.	Apple Inc.	8/24/2018	14:58	2016	Lexus	RX450h	Moving	No	No	No	2	Moderate	Rear	2016	Nissan	Leaf
4	1	3 - Apple_	Apple Inc.	Apple Inc.	9/19/2019	7:58	2017	Lexus	RX450h	Stopped ir	No	No	No	2	Minor	Front	2019	Toyota	Coro
5	1	4 - Apple_	Apple Inc.	Apple Inc.	10/15/2018	10:28	2017	Lexus	RX450h	Moving	No	No	No	2	Minor	Front	XXXX	Toyota	Cam
6	1	5 - Aurora	Aurora Inr	Aurora	1/14/2020	11:13	2017	Lincoln	MKZ	Stopped ir	No	No	No	2	None	None	1995	Jeep	Wra
7	0	6 - Aurora	Aurora Inr	Aurora Inr	6/20/2018	13:49	2017	Lincoln	MKZ	Moving	No	No	Yes	2	Minor	Rear	1997	Lexus	ES
8	1	7 - Aurora	Aurora Inr	Aurora Inr	11/2/2018	15:00	2017	Lincoln	MKZ	Moving	No	No	No	2	Minor	Rear	2000	BMW	528i
9	0	8 - Aurora	Aurora Inr	Aurora Inr	1/10/2019	14:52	2017	Lincoln	MKZ	Stopped ir	No	No	No	2	Moderate	Rear	2004	Honda	CRV
10	1	9 - Cruise_	Cruise LLC	Cruise	1/2/2020	8:24	2020	Chevrolet	Bolt	Stopped ir	No	No	No	2	Minor	Front	1998	Unknown	Econ
11	0	10 - Cruise	Cruise LLC	Cruise	1/12/2020	12:40	2020	Chevrolet	Bolt	Moving	No	No	Yes	1	Minor	Right Fron	Not Applic	Not Applic	Not A
12	1	11 - Cruise	Cruise LLC	Cruise	1/25/2020	8:10	2020	Chevrolet	Bolt	Moving	No	No	No	2	None	None	2007	Audi	Unkr
13	0	12 - Cruise	Cruise LLC	Cruise	1/17/2019	1:05	2020	Chevrolet	Bolt	Stopped ir	No	No	No	2	Minor	Rear	2010	Toyota	Prius
14	0	13 - Cruise	Cruise LLC	Cruise	10/26/2019	11:05	2020	Chevrolet	Bolt	Moving	No	No	No	2	Minor	Rear	2007	Honda	Acco
15	1	14 - Cruise	Cruise LLC	Cruise	10/27/2019	13:50	2020	Chevrolet	Bolt	Moving	No	No	No	2	Minor	Rear	2006	Honda	Civic
16	0	15 - Cruise	Cruise LLC	Cruise	10/28/2019	14:42	2020	Chevrolet	Bolt	Moving	No	Yes	No	1	None	None	Unknown	Unknown	Unkr
17	0	16 - Cruise	Cruise LLC	Cruise	11/7/2019	20:35	2020	Chevrolet	Bolt	Moving	No	No	No	2	Minor	Right Rear	Unknown	Unknown	Unkr
18	0	17 - Cruise	Cruise LLC	Cruise	11/7/2019	21:10	2020	Chevrolet	Bolt	Moving	No	No	Yes	2	Minor	Right Rear	Unknown	Unknown	Unkr
19	1	18 - Cruise	Cruise LLC	Cruise	11/9/2019	9:59	2020	Chevrolet	Bolt	Stopped ir	No	No	No	3	Minor	Rear	2016	Yamaha	YZF-I
20	0	19 - Cruise	Cruise LLC	Cruise	11/10/2019	12:55	2020	Chevrolet	Bolt	Stopped ir	No	No	No	2	Moderate	Left Side	Unknown	Volkswage	Tigua
21	1	20 - Cruise	Cruise LLC	Cruise	11/18/2019	9:45	2020	Chevrolet	Bolt	Moving	No	No	No	2	Minor	Left Front	2015	Lexus	RX35

Figure B9: Screen Capture of CSV File Data