IMAGE CLASSIFICATION USING TRANSFER LEARNING AND CONVOLUTION NEURAL NETWORKS

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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

MASTER OF SCIENCE

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ABSTRACT

In the recent years, deep learning has shown to have a formidable impact on image classification and has bolstered the advances in machine learning research. The scope of image recognition is going to bring big changes in the Information Technology domain. This paper aims to classify medical images by leveraging the advantages of Transfer Learning over Conventional methods. Three types of approaches are used namely, pre-trained CNN as a Feature Extractor, Feature Extractor with Image Augmentation, and Fine-tuning with Image Augmentation. The best pre-trained network architectures such as VGG16, VGG19, ResNet50, Inception, Xception and DenseNet are used for classification with each being applied to all the three approaches mentioned. The results are captured to find the best combination of pre-trained network and an approach that classifies the medical datasets with a higher accuracy.

ACKNOWLEDGMENTS

I would like to thank everyone who inspired me to work on the “Image Classification project”. First and foremost, I thank my adviser, Professor Simone Ludwig for introducing me to the concept of “Convolution Neural Networks” through her course “Advanced Intelligent Systems”. Also, I always admire her for the quick and prompt responses, providing me all the encouragement and support needed for completing this paperwork successfully. I would also like to thank my committee members Professor Saeed Salem, Professor Maria Alfonseca Cubero for their interest in my work and willingness to serve on my committee.

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1. INTRODUCTION

Image classification has become of increasing importance recently. With the rapid growth in Artificial Intelligence and Deep Learning, the necessity of computer vision is one of the top priorities. The future of Image recognition and analysis is gaining momentum and is surely going to change the world in the days to come.

1.1. Understanding of a Neural Network

Neural Networks is one of the most popular machine learning algorithms at present. It outpaces many other peer algorithms in solving complex problems with speed and accuracy.

1.1.1. Basic Building Block of Neural Networks – "Neuron"

From the biological definition, a neuron is the basic working unit of the brain that takes sensory input from the external world and transmits the response to other nerve cells, muscle or gland cells to perform the respective action [2]. In simple terms, it receives an input signal, process it and delivers an output signal.

Similarly, a neuron in machine learning is defined as a placeholder for a mathematical function, that takes input and performs the given function on them to provide an output [2][3]. The function used in neuron is generally termed as activation function.

Figure 1 describes X1, X2, X3 as inputs fed to a neuron. It delivers a result output after applying the function on the inputs given.

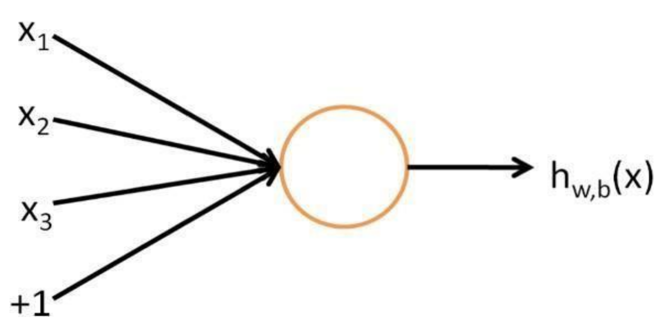


Figure 1: Basic Neuron [2]

1.1.2. Neural Network

The fundamental blocks in Neural networks are called layers. A layer is a collection of neurons that takes an input and provide an output. Each neuron has its own function and the inputs are processed layer by layer [2].

Figure 2 describes the leftmost layer as the input layer, rightmost layer is the output layer and the middle layer is called hidden layer. The number and type of hidden layers differ according to the problem. If the neural network has more than 3 or 4 hidden layers, it is called as Deep Neural Network.

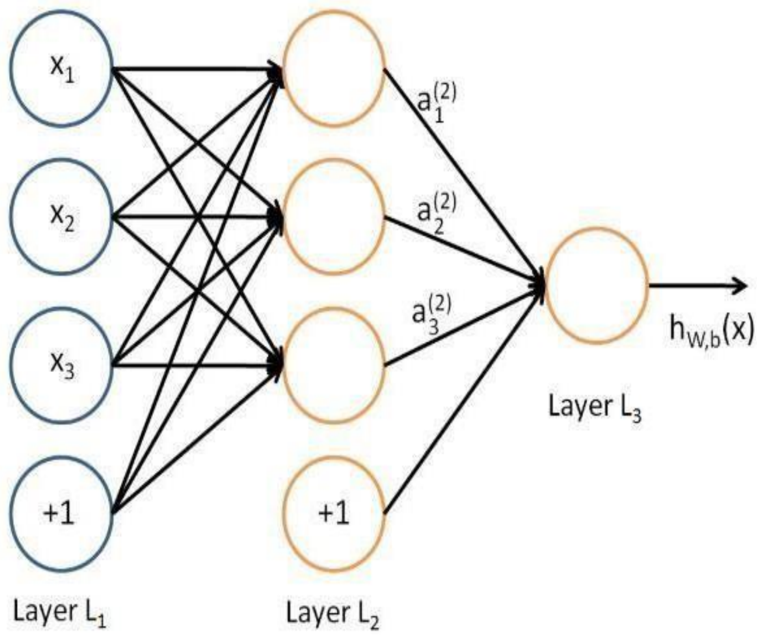


Figure 2: Simple Neural Network [2]

1.2. Composition of a Convolution Neural Network

The general activation functions used in most neural networks are step, sigmoid, tanh, ReLU and leaky ReLU. Instead of these activation functions, if we use convolution and pooling functions as activation functions in the hidden layers of the neural network, then it is called as Convolution Neural Network.

The hidden layers that use convolution or pooling function as activation function is called convolution layer or pooling layer respectively. Figure 3 describes the convolution layers, pooling layers and fully connected layer together that forms a Convolution Neural Network.

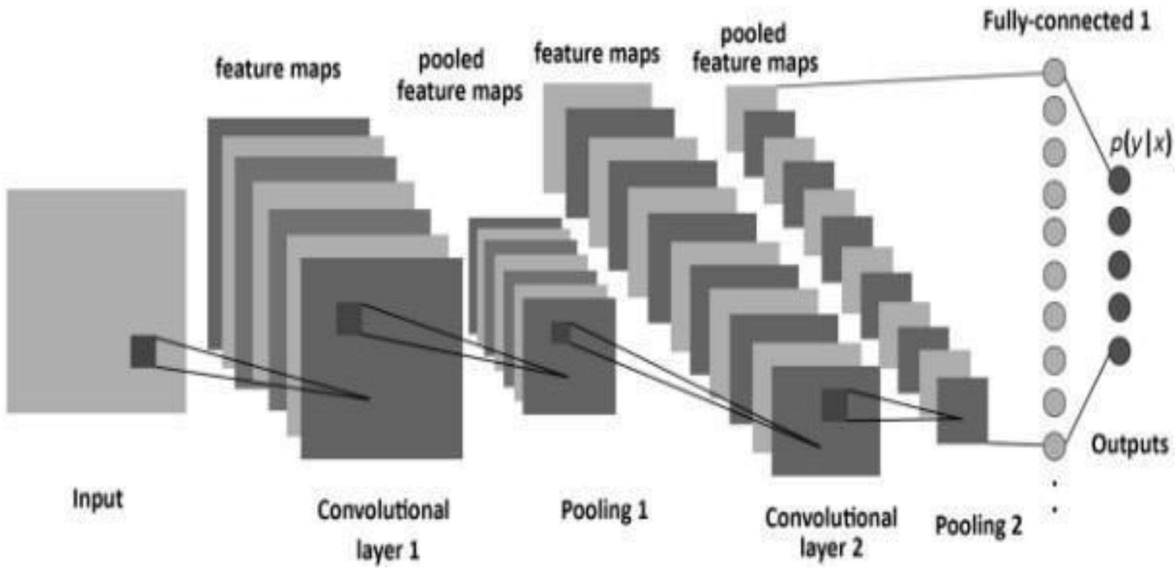


Figure 3: Convolution Neural Network Layers [2]

1.3. Transfer Learning

Using the conventional model for Image classification, we need lots of data to train the network. Although, there is the ImageNet dataset with millions of data available, we may not find the necessary amount of data for all domains. In this scenario, we can use the Transfer Learning technique, which uses pre-trained Neural Networks and uses the obtained weights on new data [4]. The idea of Transfer Learning is that, if we need to classify Task1 images but do not have enough data to train the neural network, then we find a related Task2 that has vast data and train the neural network on it [4][6]. Then, we use the whole model or few layers as desired from the Task 2 to solve Task 1.

Figure 4 describes the earlier layers of ConvNet that deals with generic features such as edge detectors, texture detectors, patterns, etc. The later layers to the end of the network become more specific to the details of the image dataset [7]. Here come the advantages of Transfer Learning. We will fix/freeze the earlier layers of the pre-trained network and retrain the rest of the layers with fine tuning of backpropagation. Instead of training our network from the first layer, we just transfer the weights already learned by a pre-trained network such as VGG16 and save time and efforts [8][9].

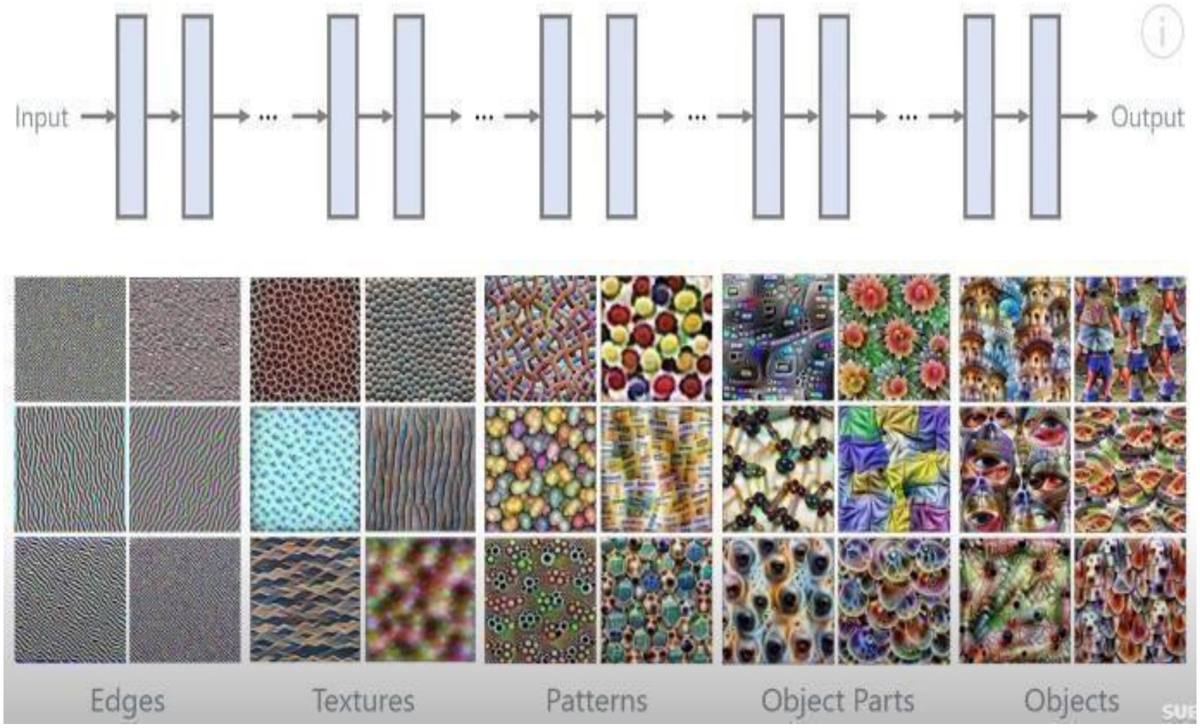


Figure 4: Difference between Initial Layers and Later Layers [4]

2. RELATED WORK

The growing medical usability of Image classification attracts the attention of many researchers to do further investigation on the concepts of Convolution Neural Networks. One of the ways of investigation is the detection of pneumonia from X-ray chest images using Transfer Learning technique. Kermany et al. in [10] presented medical diagnoses and treatable diseases by using image-based deep learning models to detect or classify different medical datasets. They used the Inception V3 architecture for pre-training the model on the ImageNet dataset. Here, the convolution layers were frozen and used as fixed feature extractors. Initially generated bottleneck features from training on the ImageNet dataset and utilized them to train and classify X-ray images. The testing accuracy for chest X-rays for pneumonia detection was 92.80 %.

Stephen et al. in [11] presented an efficient deep learning approach to pneumonia classification in healthcare. The authors proposed a deep learning model with 4 convolutional layers and 2 dense layers in addition to classical image augmentation. They did not use any pre-trained networks rather developed a CNN from scratch to extract features from a given chest X-ray image and classify it to determine if a person is infected with pneumonia. They used the image augmentation concept to mitigate the reliability and interpretability challenges often faced when dealing with medical imagery and achieved 93.73% testing accuracy.

Wu et al. in [12] presented a model to predict pneumonia with chest X-ray images based on convolutional deep neural learning networks and random forest. Initially, the authors used adaptive median filtering to improve the quality of images. Then, established the CNN architecture based on Dropout to extract deep activation features from each chest X-ray image. Finally, employed the Random Forest classifier based on GridSearchCV class as a classifier for deep activation features in CNN model. The authors achieved 97 % testing accuracy.

Liang and Zheng in [13] presented a transfer learning method with a deep residual network for pediatric pneumonia diagnosis. The authors a deep learning model with 49 convolutional layers and 2 dense layers and achieved 96.70% testing accuracy. Their paper has shown that deep learning does not require feature processing of input data compared to traditional supervised pattern recognition methods, and model performance is not limited by the medical diagnostic experience owned by the designer, thus having an unparalleled advantage.

Lung cancer accounts for 26 % of all cancer deaths in 2017, accounting for more than 1.5 million deaths. Thus, Nobrega et al. in [14] proposed to explore the performance of deep transfer learning to classify pulmonary nodule malignancies. In this work, they have used a convolutional neural network such as VGG16, VGG19, MobileNet, Xception, InceptionV3, ResNet50, Inception-ResNet-V2, DenseNet169, DenseNet201, NASNetMobile and NASNetLarge, where they were used to extract parameters from an image database of the lung. The characteristics were classified using Naive Bayes, Perceptron multilayer, support vector machine, Near Neighbors and Random Forest and achieved 95.3% testing accuracy.

All the above-related works used the chest X-ray images for pneumonia classification in different methodologies. The main difference between our proposed model and other related works according to literature surveys; this paper considered one of the methods to use the data augmentation to generate more images and make the proposed model immune from a smaller number of datasets. We used feature extraction with fine-tuning that re-trains the weights in ‘unfreeze layers’ by backward propagation. Also, we showed the implementation using the top best pre-trained networks of Transfer Learning and compared all of them in terms of accuracy, precision, sensitivity, specificity and F1-score.

3. APPROACH

3.1. How a Computer See an Image

A computer understands an image using numbers for each pixel. The smallest element of an image is called a pixel, which is basically a dot as shown in Figure 5. If an image is said to have resolution 250*350, it means it's 250 pixels wide and 350 pixels high [16]. We can describe images into two types according to their color, namely colored and gray scale (black and white).

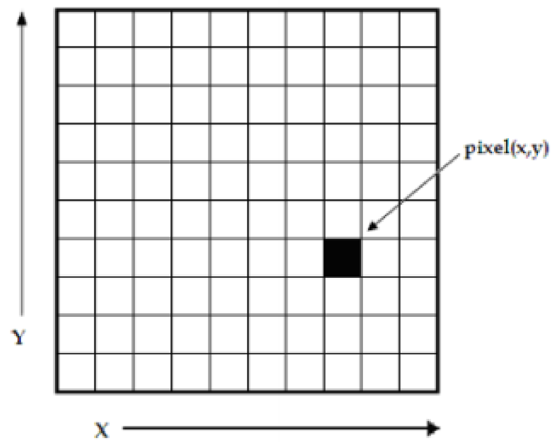


Figure 5: Color Pixel Visualization [16]

3.1.1. Colored Images

In color images, pixels are represented in the RGB color model. RGB stands for **R**ed **G**reen **B**lue and represents a tuple of three components. Each component can take a value between 0 and 255, where the tuple (0,0,0) represents black and (255,255,255) represents white [17]. All colors that humans perceive are various combinations of red, green and blue. Figure 6 describes a few more examples of color notations in RGB model. If an image is represented as 250*350*3 pixels, the last pixel indicates the three components of the RGB tuple. We can convert a colored image to gray scale and vice-versa by applying transformation on the tuple values respectively.

Color	RGB value
Red	255, 0, 0
Orange	255, 128, 0
Pink	255, 153, 255

Figure 6: Color Code Composition [1]

3.1.2. Gray Scale Images

In grayscale (black and white) images, each pixel is a single number representing the amount of light, or intensity, it carries. In most of the cases, the range of intensities are used which are from 0(black) to 255(white). Everything between 0 and 255 is various shades of gray. Figure 7 describes the clear view of a gray scale image as seen by a computer. Colored images can be converted to gray scale and vice-versa by altering the RGB tuple components [18].

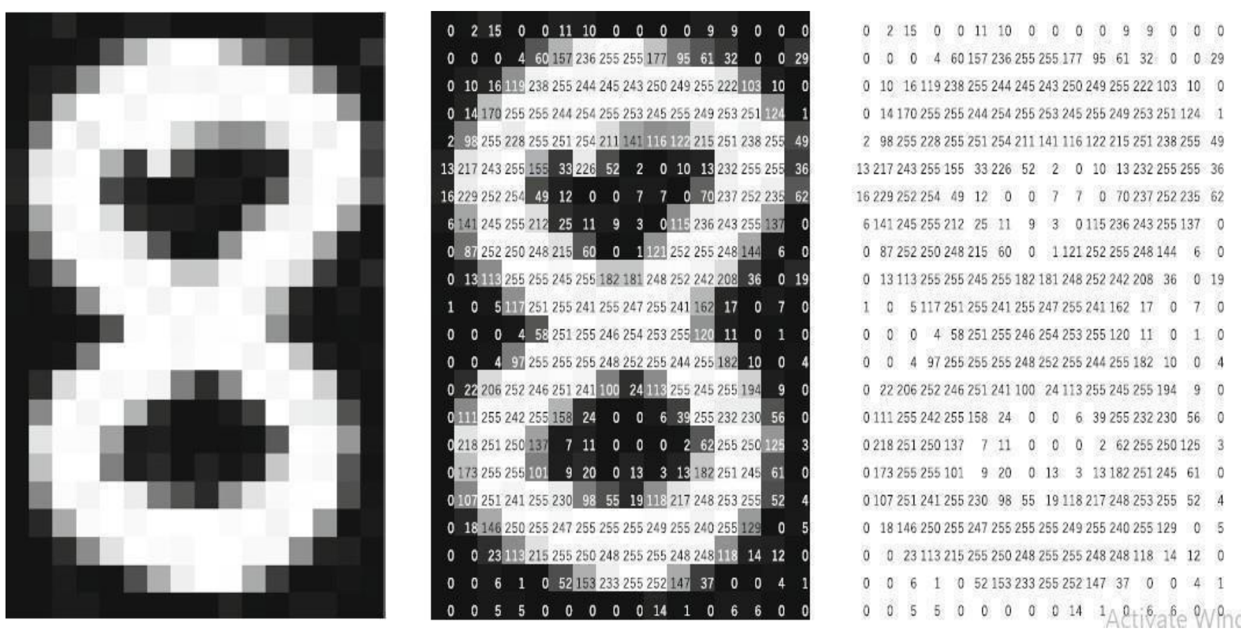


Figure 7: Gray Scale Representation of Images [19]

3.2. Convolution Neural Networks

CNNs are a combination of convolution, ReLU, pooling and fully connected layers [19]. If we need to predict ‘X’ vs ‘O’ images, there can be trickier cases where images are deformed. We need to classify all images to either ‘X’ or ‘O’ irrespective of deformations. Using normal techniques, computers compare images for classification and the deformed images cannot be classified. Here comes the use of CNNs that can classify normal as well as deformed.

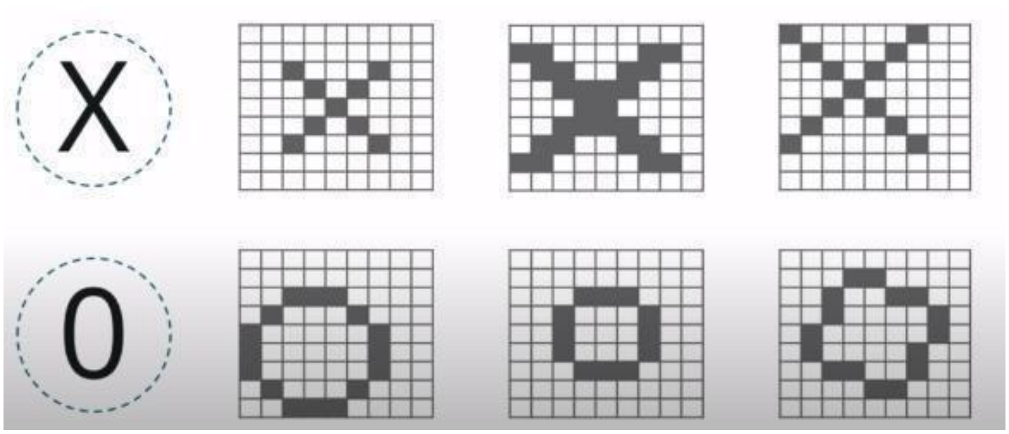


Figure 8: Deformed Images of ‘X’ and ‘O’ [19]

3.2.1. Assigning Values According to Color

As the computer understands an image using numbers at each pixel and the intensity is same throughout the ‘X’ or ‘O’, let’s use value 1 for black pixel and -1 for white pixel as shown in Figure 9 [19].

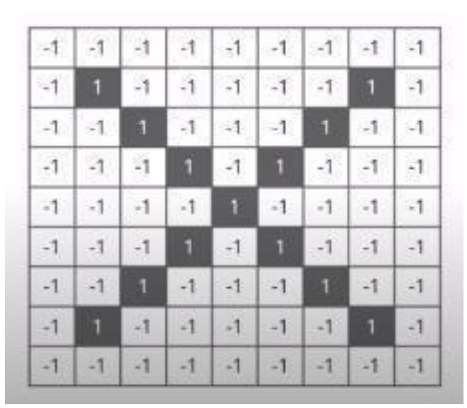


Figure 9: Assigned Values for ‘X’ [19]

3.2.2. Selecting Features for Convolution

CNN compares images piece by piece. The pieces that it looks for are called features. By finding rough feature matches, in roughly the same position in two images, CNN gets a lot better at seeing similarity than whole-image matching schemes. Figure 10 describes the three features or filters used in this case [19].

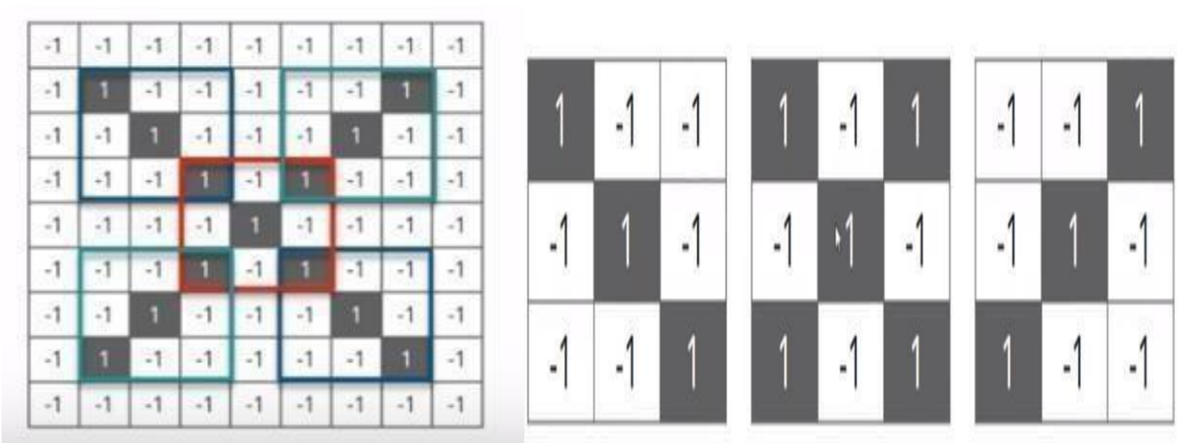


Figure 10: Selecting Features for Convolution [19]

3.2.3. Convolution Layer

Here we will move each feature/filter to every possible position on the image. Multiply each image pixel by the corresponding feature pixel and finish a result matrix as described in Figure 11. The next step is to add all the elements in the result matrix and divide by total number of pixels in the feature. To create a map put the value of a filter at that respective place as shown in Figure 12.

Similarly, move the filter/feature to every other positions of the image and will see how the feature matches that area. Finally, we will get an output as shown in Figure 13 for one feature. After performing the same process for the other two filters as well, we get the convolution results for all the features as shown in Figure 14.

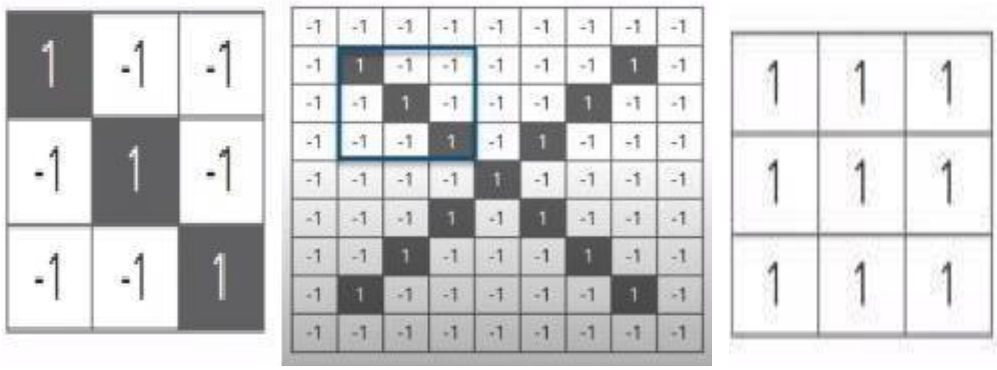


Figure 11: Convolution Step 1 [19]

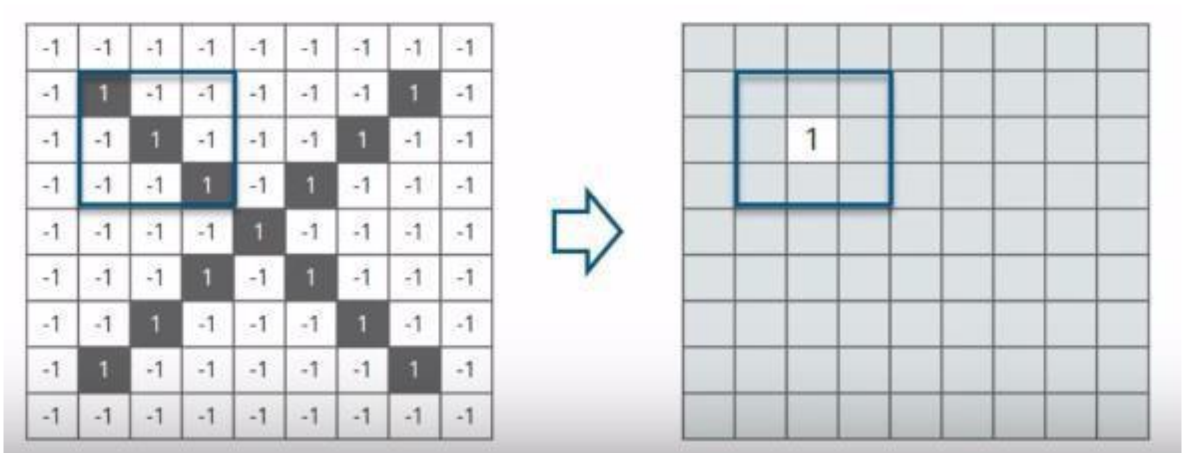
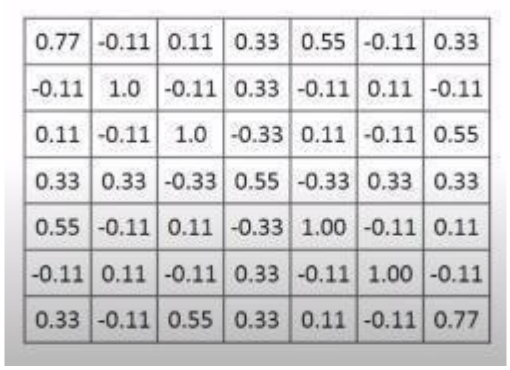


Figure 12: Convolution Step 2 [19]



0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.0	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.0	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

Figure 13: Convolution Step 3 [19]

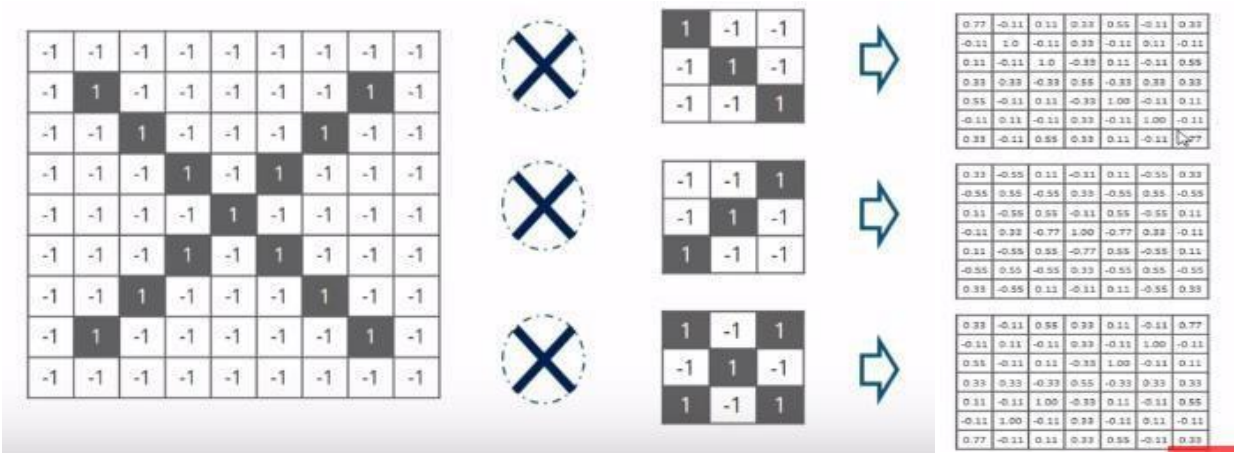


Figure 14: Convolution Step 4 [19]

3.2.4. ReLU Layer

Rectified Linear Unit (ReLU) is an activation function that activates a node if the input is above a certain quantity. While the input is below zero, the output is zero, but when the output rises above a certain threshold, it has a linear relationship with the dependent variable as shown in Figure 15 [20].

In this layer we remove every negative value from convolution results and replace it with zeros. This is done to avoid the values from summing up to zero. The output for one feature looks like as shown in Figure 16. Likewise, we must calculate ReLU activation results for all features.

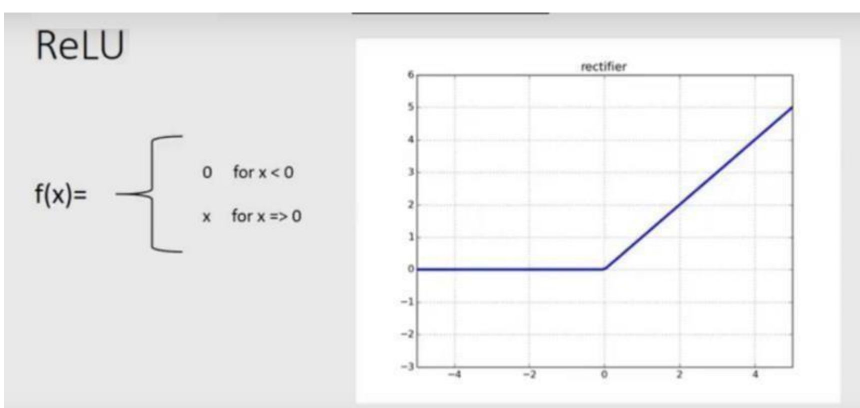


Figure 15: ReLU Function [19]

Figure 16: ReLU Step [19]

3.2.5. Pooling Layer

In this layer, the image stack is shrunk into a smaller size. We use the max pooling function here. The steps include picking a window size (usually 2 or 3), pick a stride (usually 2), walk the window across the ReLU results, from each window take the maximum value. Let us see results after performing pooling with a window size 2 and a stride 2 on first filtered image.

In the first window the maximum or highest value is 1, so we track that and move the window two strides. Figure 17 describes the pooling of one 2*2 window.

After doing the pooling for entire image, we get the result as shown in Figure 18. We can see that the result matrix got reduced from 7*7 to 4*4 of size. Repeat the process for all three outputs that we got after ReLU layer and we get 4*4 matrix for each respectively.

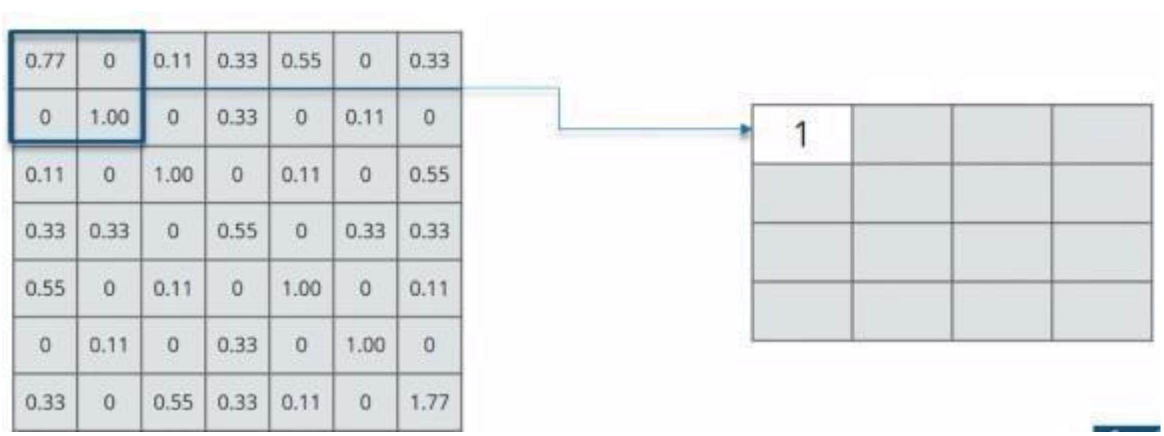


Figure 17: Pooling Layer Step 1 [19]

Figure 18: Pooling Layer Step 2 [19]

3.2.6. Stacking Up the Layers

After passing through Convolution, ReLU and Pooling we get the 4*4 matrices from the input image [21] as shown in Figure 19.

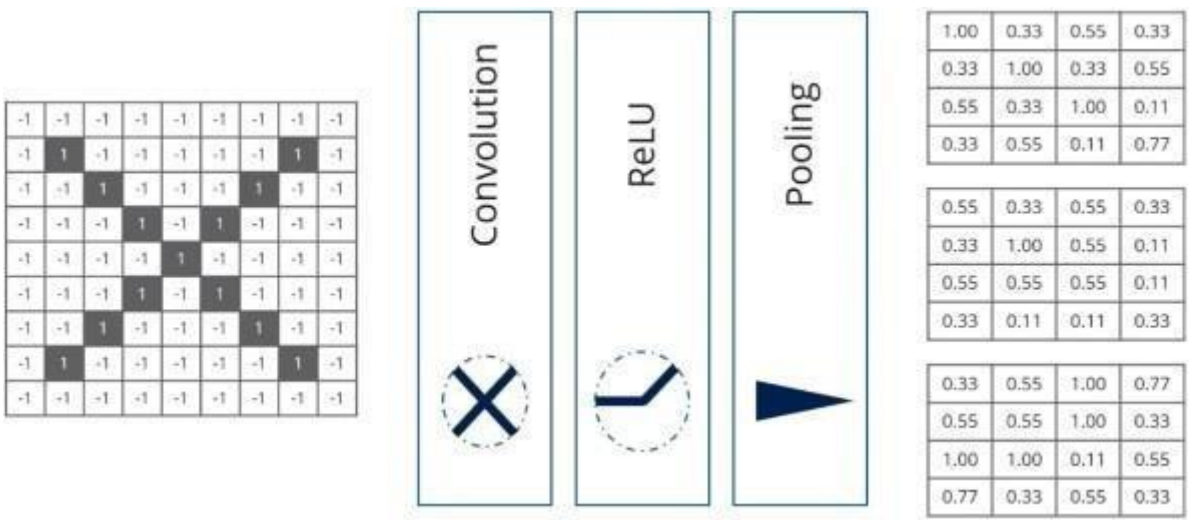


Figure 19: Stacking Up of Layers Step1 [19]

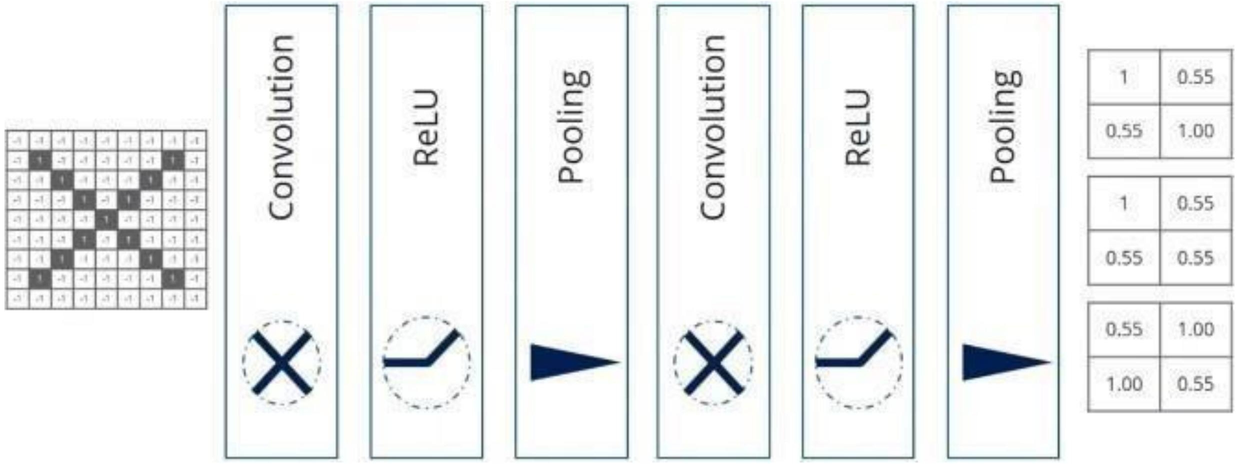


Figure 20: Stacking Up of Layers Step 2 [19]

3.2.7. Fully Connected Layer

This is the final layer where the actual classification happens. Here we take our filtered and shrunk images and put them into a single list or a vector as shown in Figure 21.

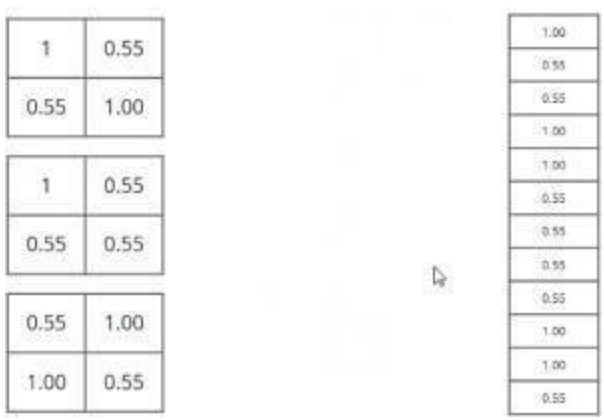


Figure 21: Fully Connected Layer [19]

3.2.8. Output

We can see that certain values in the list are high for ‘X’ and if we repeat the entire process for ‘O’ there will be certain different values which are high. For ‘X’ 1, 4, 5, 10, 11 vectors are high and for ‘O’ 2, 3, 9, 12 element vectors are high. Now, as shown in Figure 22, the model is trained with the vectors to classify between ‘X’ and ‘O’.

Consider we have given a new input image for classification. That image passes through all the layers and got the corresponding 12 element vector as shown in Figure 23. We compare with the list of 'X' and 'O'. For 'X' there are certain values which are high (1,4,5,10,11) and sum these vectors which is 5. Sum the corresponding vectors of input image which is 4.96. Divide by 5 and we get 0.91. Similarly, for 'O' we get 0.51. As 0.91 is greater than 0.51, the input image is classified as 'X'.

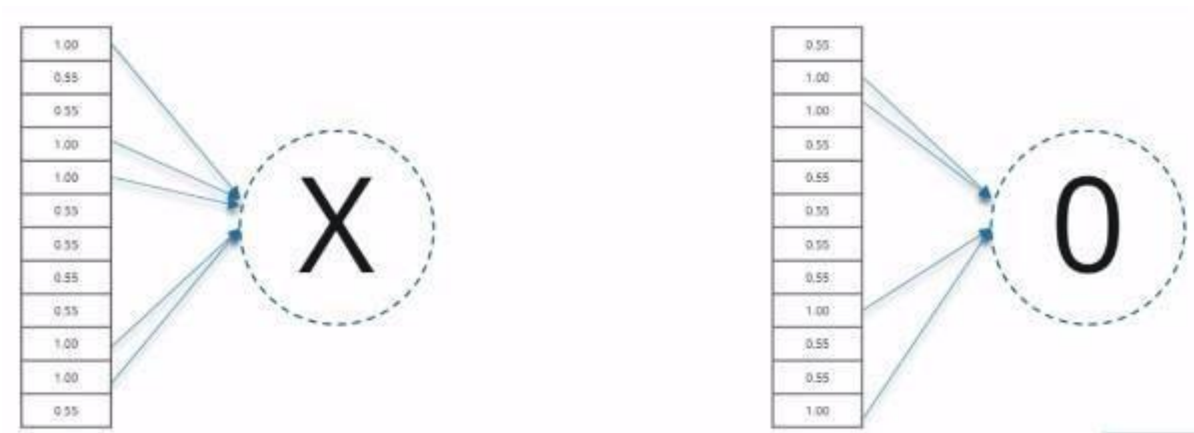


Figure 22: Output Step 1 [19]

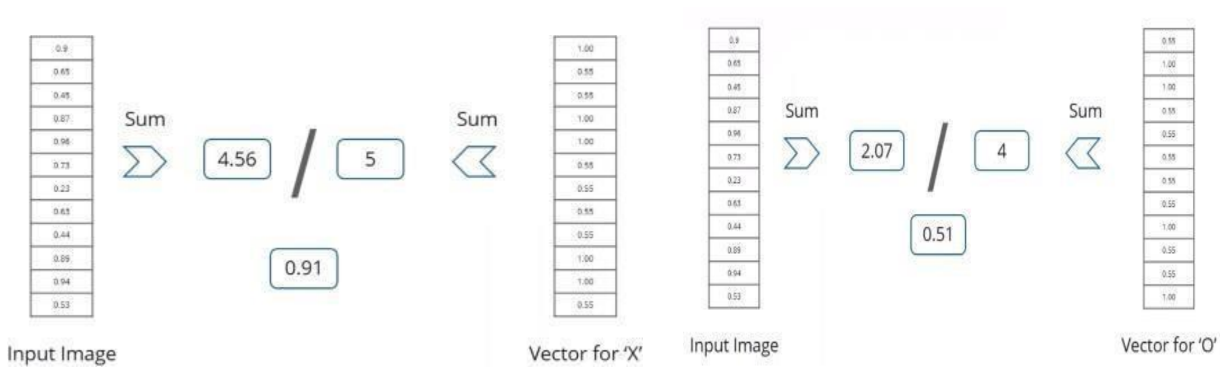


Figure 23: Output Step 2 [19]

3.3. Transfer Learning

In context of deep learning, most models need lots of data, and obtaining a large amount of labeled data for a variety of domains can be difficult, considering the time and effort it takes to label the data. Although there is ImageNet dataset with millions of data, getting data for every domain is tough. While there are state-of-the-art models which give high accuracy, they would be only on specific datasets and when used on new similar task, they suffer a significant loss. This forms the basis for transfer learning which used knowledge gained from pre-trained networks and use it to solve new similar problems [22].

3.3.1. Why to Use Transfer Learning

Consider Figure 24 for training with label as an elephant. It is of size 225*150 pixels taking color pixel as a single component. As ‘X’ and ‘O’ are simple, we just used three filters. Here, we must take hundreds or even thousands of filters for convolution. If each filter is of size 3*3, it must perform convolution on the given image which is 225*150 pixels. That is, each feature generates a 75*50 size matrix. All filters together generate thousands of similar matrices which takes lot of computational time and memory. Figure 25 shows the sample computations visual for each layer. Apart from this, there is still ReLU and pooling functions in each block as shown in Figure 26. In summary, if we have 3000 training images of 228*150 pixels each, the computations for the initial block are as shown in Table 1.

The initial layers perform a lot of computations and as passed to the next block the number of computations decreases due to the convolution and pooling in the previous blocks. To train the model on one image, the computations of first block are as shown in Table 1. If the training images are around 3,000, these computations are multiplied by the same amount which need huge memory, time and computational power.

Here comes the use of pre-trained networks which are already trained on millions of ImageNet datasets and can be used instantly for classification. However, all types of images are not available in ImageNet and the pre-trained networks become obsolete if they need to classify new set of images which are out of scope of the ImageNet datasets.

The solution for this is to use Transfer Learning. It enables us to utilize knowledge from previously learned tasks and apply on new similar tasks. In computer vision domain, the initial blocks of CNN extract certain low-level features such as edges, shapes, corners, intensity etc. As we know that initial blocks use more computational power, we transfer the knowledge (features, weights) of them from a pre-trained network and utilize to classify new images. The last blocks in CNN are more specific to image details and hence we freeze the top layers and use the bottom layers as per the problem.

Figure 24: A Sample Image

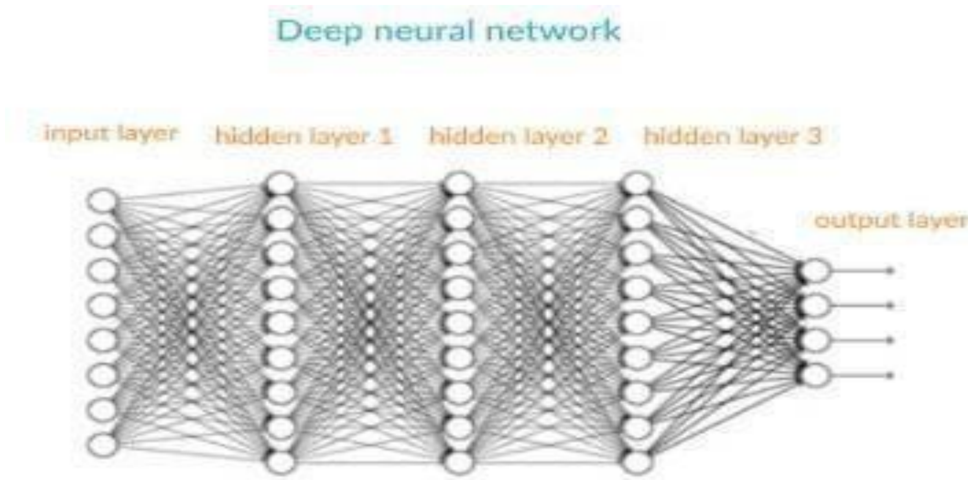


Figure 25: Deep Neural Network [21]

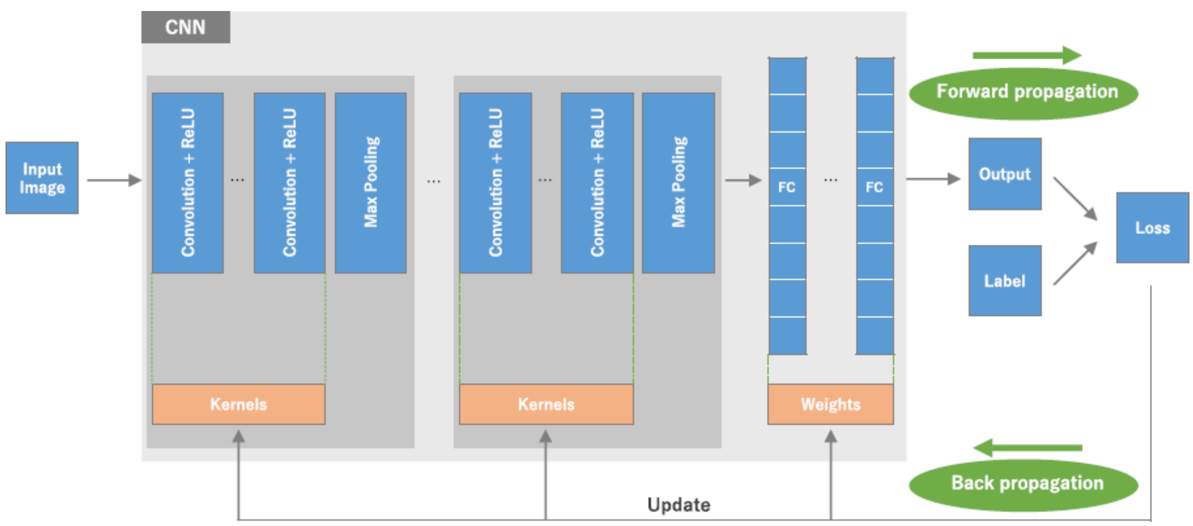


Figure 26: Complete Picture of CNN [41]

Table 1: Demonstration of Layers in Convolution Neural Network

	Block 1		
For One training image of 225*150 pixels		**Input**	**Output**
	Convolution Layer	let 100 number of filters	Hundred 75*50 matrices
	ReLU Layer	Hundred 75*50 matrices	Hundred 75*50 matrices
	Pooling layer	Hundred 75*50 matrices	Hundred 36*25 matrices

3.4. Architectures of Pre-trained Models

In all pre-trained networks, we use all the convolution layers for feature extraction. We then replace the fully connected and dense layer with our own layers to classify the images as normal or pneumonia. With fine-tuning in place, we unfreeze last couple of blocks before fully connected layers. These blocks adjust their weights with respect to loss function using backpropagation technique. Let us have a look at a couple of architectures [25].

3.4.1. VGG16 Architecture

This is a 16-layer (convolution and fully connected) network built on the ImageNet database for the purpose image classification. Figure 27 describes the architecture of the model.

From the image, we can see that there are 13 convolution layers using 3*3 filters along with max pooling and two fully connected hidden layers of 4,096 units in each layer followed by a dense layer of 1,000 units, where each unit represents one of the image categories in the ImageNet database.

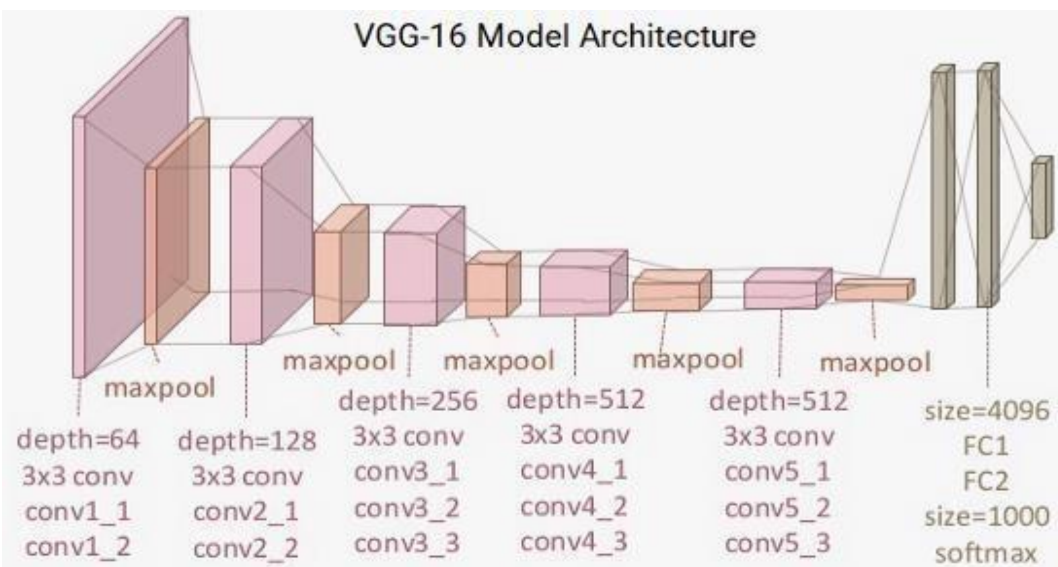


Figure 27: VGG16 Architecture [43]

3.4.2. VGG19 Architecture

This is a 19-layer network with 16 convolution layers along with pooling layers, two fully connected layers and a dense layer as shown in Figure 28.

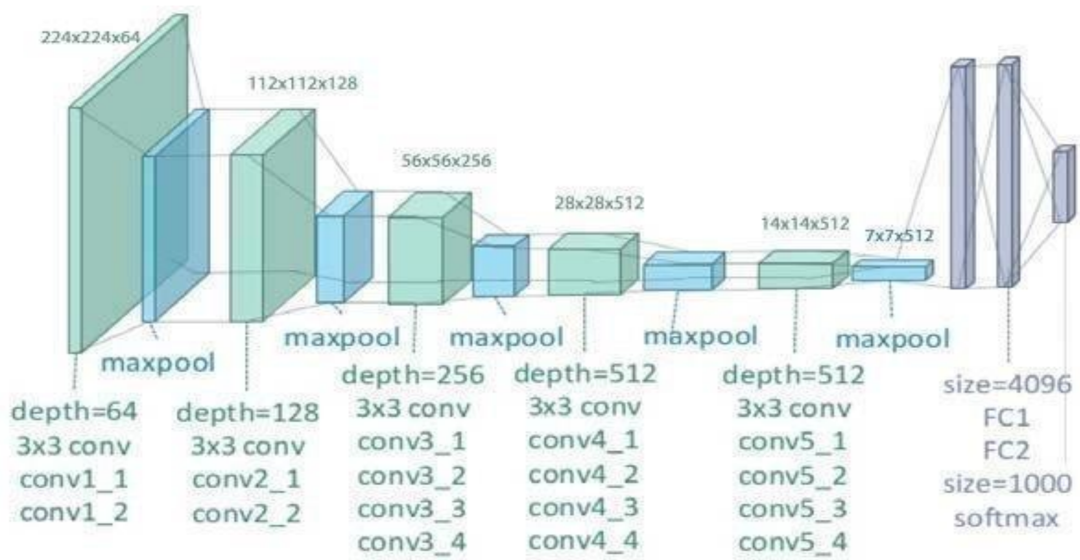


Figure 28: VGG19 Architecture [42]

3.4.3. ResNet50 Architecture

Figure 29 describes the architecture of ResNet50, which is a 50-layer deep neural network. Similarly, Inception, Xception and DenseNet pre-trained networks have their respective convolution and pooling layers with subtle changes in number of layers, pixels of filters and layers.

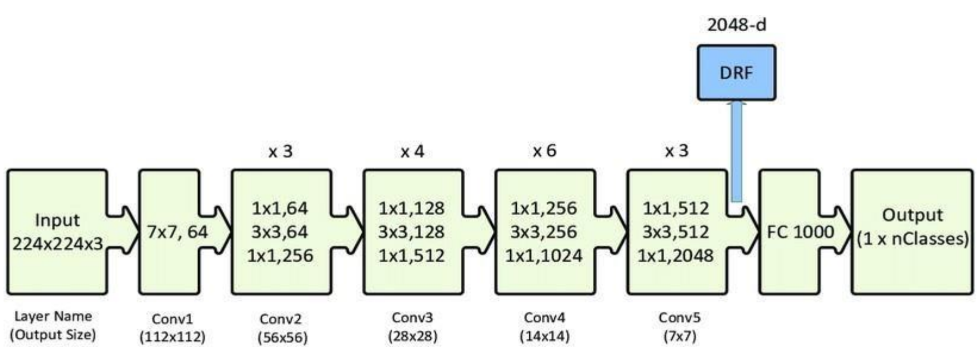


Figure 29: ResNet50 Architecture [42]

3.5. Leveraging Transfer Learning with Pre-trained CNN Models

Let us consider the transfer learning with the pre-trained VGG-16 model. We perform the classification using three approaches as follows [26].

3.5.1. Feature Extractor

In this method, we just use it as a simple feature extractor by freezing all the five convolution blocks to make sure their weights do not get updated after each epoch.

3.5.2. Feature Extractor with Image Augmentation

To overcome small training data problem in the first approach, we use the advantage of Image Augmentation here. It is the process in which we apply image transformation operations such as rotation, shearing, translation, zooming, andso on, to produce new, altered versions of existing images. Due to these random transformations, we do not get the same images each time and this results in more training image datasets. With more training data we perform the feature extraction and image classification [27].

3.5.3. Fine-Tuning with Image Augmentation

For the last model, we will apply fine-tuning to the model, where we will unfreeze the last two blocks (Block 4 and Block 5 in case of VGG-16 shown in Figure 30) so that their weights get updated in each epoch. This is a more involved technique as we selectively retrain some of the previous layers instead of just replacing the final layer [28].

Thus, we are mostly concerned with leveraging the convolution blocks of the pre-trained model and then flattening the output (from the feature maps) so that we can feed it into our own dense layers for our classifier. Figure 30 describes a better block diagram visual perspective [29].

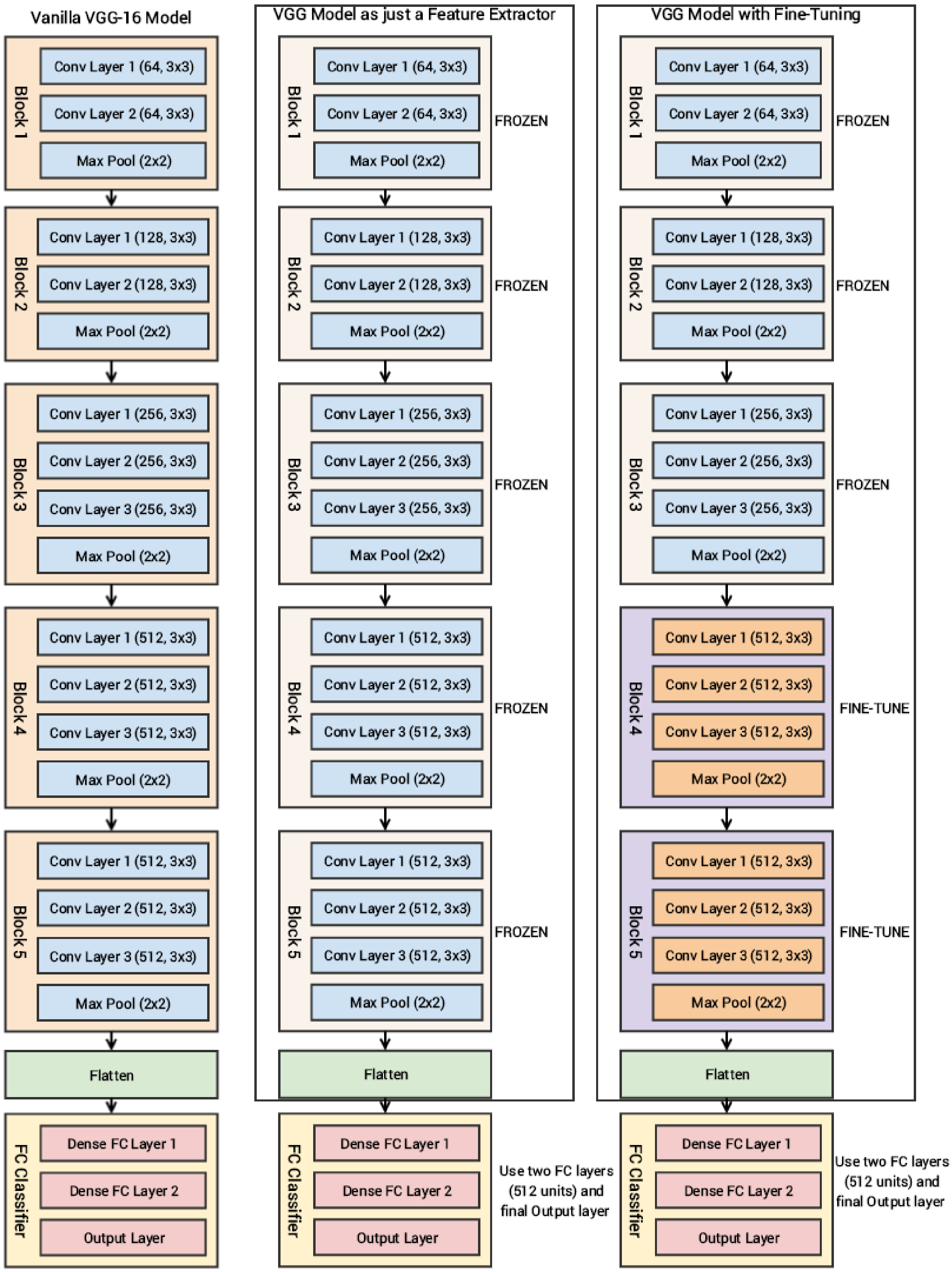


Figure 30: Block Diagram Showing Transfer Learning Strategies on VGG16 Model [43]

4. EXPERIMENTS AND RESULTS

4.1. Data Composition

4.1.1. Initial Datasets

The initial raw datasets are unlabeled images with the number of images in each category as described in Table 2.

Table 2: Initial Datasets

	Number of Images	
Data type	**NORMAL**	**PNEUMONIA**
Test	234	390
Train	1341	3875
Val	8	8

4.1.2. Labelled and Organized Datasets

In neural networks, better accuracies can be achieved with more training data. A good number of validation data is required to calculate the accurate validation loss after each epoch and backpropagate the error to correct the weights in the desired layers. The test data should be maintained to check the results and performance accuracy. Neural networks need the label dataof each image to train, validate and test them appropriately. With these points in mind, the data is split proportionally as shown in Table 3, and the images are labelled as NORMAL and PNEUMONIA, respectively.

Considering the VGG-16 model to demonstrate the experiments, the datafile has test, train and validation data in the test, train and val subfolders. Each category (test/train/val) of the data folder has NORMAL/PNEUMONIA subfolders that contain the respective images.

Create train, test and validation lists. Append images locations to these lists according to labels. Example: x_train contains all NORMAL Images from training dataset and y_train contains all PNEUMONIA images of training dataset. Figure 31 describes datasets count for each category.

Resize and convert the images to array using the python inbuilt library ‘array_to_img’. Store the arrays in separate lists for training and validation. Split the labels and store in labels list. Training dataset shape and Validation dataset shape now is: (5000, 150, 150, 3) and (80, 150, 150, 3) respectively.

Scale the images and transform the labels using ‘LabelEncoder’ library. Import and Load the chosen model with ‘imagenet’ as weights.

Table 3: Labelled and Organized Datasets

	Number of Images		
Data type	**NORMAL**	**PNEUMONIA**	**Total**
Test	300	390	690
Train	1200	3800	5000
Val	80	80	160

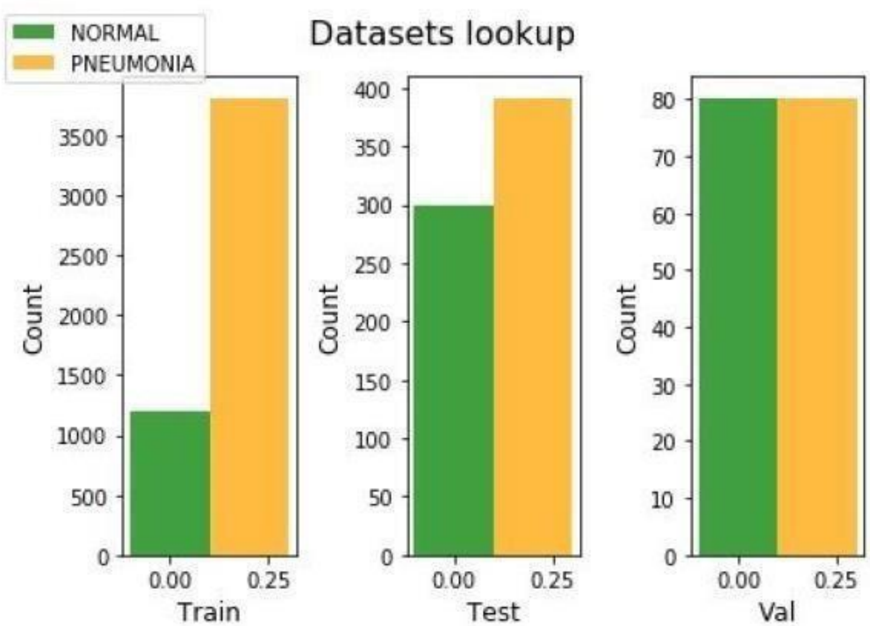


Figure 31: Datasets

4.2. Performance Metrics Setup

The labels of all test data are available for the classification. The new predicted labels are then compared with the existing labels [33]. From the comparison we find the measures as described in Table 4.

- True positive: Pneumonia images correctly identified as pneumonia
- False positive: Normal images incorrectly identified as pneumonia
- True negative: Normal people correctly identified as Pneumonia
- False negative: Pneumonia people incorrectly identified as Normal

Table 4: True Positive, True Negative, False Positive, False Negative

		Predicted Class	
		NORMAL	**PNEUMONIA**
True Class	**NORMAL**	True Negative (TN)	False Positive (FP)
	PNEUMONIA	False Negative (FN)	True Positive (TP)

4.2.1. Accuracy and Precision

Accuracy is how close a measured value is to its true value. Precision is how close all the measured values are to each other. In other words, accuracy is the ratio of the number of correct classifications to the number of all classifications. Precision is the ratio of true Pneumoniaimages to all Pneumonia predictions. Figure 32 describes the difference of the same.

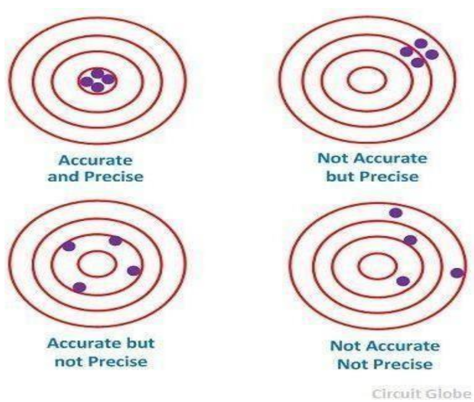


Figure 32: Accuracy vs. Precision [44]

4.2.2. Recall/Sensitivity and Specificity/Selectivity

Sensitivity, also called as true positive rate is the ratio of true positives to total number of actual positives [34]. Similarly, specificity, also called as true negative rate is the ratio of true negatives to total number of actual negatives. In simple terms, if 100 images are of pneumonia and we predict 90 of them as pneumonia (true positive), sensitivity is said to be 90%. Similarly, if 100 images are healthy and we predict 85 of them as healthy (true negative), specificity is 85%.

4.2.3. F1-Score

If a model accuracy is 90%, it is high enough to consider it as an accurate model. Yet, there are 10% patients whose pneumonia results are incorrect, and this is too high a cost. Hence, we also consider F1-score as a metric that gives a better measure of incorrectly classified cases [35]. This is calculated as a harmonic mean of precision and recall. Accuracy is used when true positives and true negatives are more important. While the F1-score is a better metric when the class distribution is unequal and false positives and false negatives are more crucial [36]. Figure 33 describes all the metrics formulae.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

$$F - score = \frac{2}{1/precision + 1/recall}$$

$$specificity = \frac{TN}{TN + FP}$$

$$sensitivity = \frac{TP}{TP + FN} = recall$$

Figure 33: Accuracy, Precision, Recall, Specificity, F1-Score Formulae [34]

4.2.4. Confusion Matrix

A Confusion Matrix in a classification problem is the tabular representation of prediction results with count values broken down by each class [37]. As the name suggests, it shows how a classification model performs when making predictions. It gives insight into the errors being made by the classifier and the type of errors. For instance, Figure 34 shows a confusion matrix with 5 different classes and 12 images of Asphalt that are falsely classified as Building images [39].

Truth

Predicted	Asphalt	Concrete	Grass	Tree	Building	Total
Asphalt	2385	4	0	1	4	2394
Concrete	0	332	0	0	1	333
Grass	0	1	908	8	0	917
Tree	0	0	0	1084	9	1093
Building	12	0	0	6	2053	2071
Total	2397	337	908	1099	2067	6808

Figure 34: Confusion Matrix Demonstration [45]

4.2.5. ROC Curve

A receiver operating characteristics curve, or ROC curve, is a graphical representation of the true positive rate (sensitivity) vs. the false positive rate (1 - specificity) [38]. It depicts the trade-offs between true positives (benefits) and true negatives (costs). As shown in Figure 35, the best possible prediction would yield a point on the upper left coordinate (0, 1) representing 100% sensitivity (no false negatives) and 100% specificity (no false positives) [40]. The diagonal line that divides the ROC space from the left bottom to the right corners is called line of no-discrimination. A random guessing of classification would yield results on this line. The points above and below the line represent better and worse classification results, respectively.

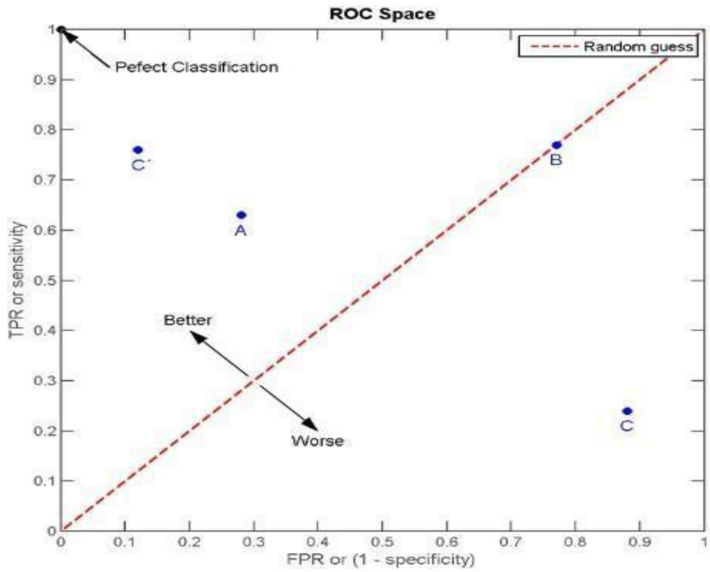


Figure 35: ROC Curve Example [40]

4.3. Three Methodologies of Classification

4.3.1. Pre-trained CNN Model as Feature Extractor

Freeze all the convolution layers using the python libraries and use the pre-trained network as just for feature extraction of the images.

The output is as shown in Figure 36. It shows all the layers are frozen as expected. The last activation feature map is the output from 'block5_pool' that gives the bottleneck features. All the training and validation dataset features are extracted, flattened and fed as input to the classifier.

Build a classifier that takes the flattened bottleneck features as input and performs the classification. Train the model using 'model.fit' selecting the number of epochs, batch size, training data and validation data. Save the model to use for classifying the testing images.

model.save('chest_xray_fulldataset/NORMAL_PNEUMONIA_tlearn_basic_cnn.h5')

	Layer Type	Layer Name	Layer Trainable
0	<keras.engine.topology.InputLayer object at 0x7f26c86b2518>	input_1	False
1	<keras.layers.convolutional.Conv2D object at 0x7f277c9fc080>	block1_conv1	False
2	<keras.layers.convolutional.Conv2D object at 0x7f26c86b26d8>	block1_conv2	False
3	<keras.layers.pooling.MaxPooling2D object at 0x7f26c86e6c88>	block1_pool	False
4	<keras.layers.convolutional.Conv2D object at 0x7f26c867dc18>	block2_conv1	False
5	<keras.layers.convolutional.Conv2D object at 0x7f26c8690f28>	block2_conv2	False
6	<keras.layers.pooling.MaxPooling2D object at 0x7f26c869e5c0>	block2_pool	False
7	<keras.layers.convolutional.Conv2D object at 0x7f26c863f828>	block3_conv1	False
8	<keras.layers.convolutional.Conv2D object at 0x7f26c863f128>	block3_conv2	False
9	<keras.layers.convolutional.Conv2D object at 0x7f26c86607b8>	block3_conv3	False
10	<keras.layers.pooling.MaxPooling2D object at 0x7f26c83d7d68>	block3_pool	False
11	<keras.layers.convolutional.Conv2D object at 0x7f26c83fd358>	block4_conv1	False
12	<keras.layers.convolutional.Conv2D object at 0x7f26c83fddd8>	block4_conv2	False
13	<keras.layers.convolutional.Conv2D object at 0x7f26c839da20>	block4_conv3	False
14	<keras.layers.pooling.MaxPooling2D object at 0x7f26c83ac1d0>	block4_pool	False
15	<keras.layers.convolutional.Conv2D object at 0x7f26c834e978>	block5_conv1	False
16	<keras.layers.convolutional.Conv2D object at 0x7f271a15eb38>	block5_conv2	False
17	<keras.layers.convolutional.Conv2D object at 0x7f26c8371d68>	block5_conv3	False
18	<keras.layers.pooling.MaxPooling2D object at 0x7f26c8314b00>	block5_pool	False
19	<keras.layers.core.Flatten object at 0x7f26c828bda0>	flatten_1	False

Figure 36: Illustration of Frozen Layers

4.3.2. Pre-trained CNN Model as a Feature Extractor with Image Augmentation

Perform image augmentation on training and validation datasets. We keep layers of CNN network frozen and generate image data using python library 'ImageDataGenertor'. Build training model on the data generators rather on the bottleneck features as in Method 1. Save the model as h5 file to be used for classifying the training data.

model.save('chest_xray_fulldataset/NORMAL_PNEUMONIA_tlearn_img_aug_cnn.h5')

4.3.3. Pre-trained Model with Fine-Tuning and Image Augmentation

Unfreeze the last two layers – ‘block5_conv1’ and ‘block4_conv1’.

```
for layer in cnn_model.layers:
    if layer.name in ['block5_conv1',
        'block4_conv1']: set_trainable = True
    if set_trainable:
        layer.trainable
        = True
    else:
        layer.trainable = False
```

Figure 37 describes that the block4 and block5 are now trainable backwards after each epoch. Use the same model with the Image generators as in Section 4.1.2 to train the model. Save the model for classifying the testing data.

```
model.save('chest_xray_fulldataset/NORMAL_PNEUMONIA_tlearn_finetune_img_aug_cnn.h5')
```

Plot the changes of the validation accuracy after each epoch. Load the test images. Scale them, split the labels and save them to separate lists. Load the ‘.h5’ file and input the test data to get the classification. Choose random test images and show their actual and predicted labels. Plot confusion matrix that shows the True Normal and True Pneumonia classification. Calculate the accuracy, precision, sensitivity, specificity and F-1 score. Create a 2d array with all the accuracies updated to it. Visualize it as a DataFrame and plot the bar diagram of all accuracies for each pre-trained network.

	Layer Type	Layer Name	Layer Trainable
0	<keras.engine.topology.InputLayer object at 0x7f26c86b2518>	input_1	False
1	<keras.layers.convolutional.Conv2D object at 0x7f277c9fc080>	block1_conv1	False
2	<keras.layers.convolutional.Conv2D object at 0x7f26c86b26d8>	block1_conv2	False
3	<keras.layers.pooling.MaxPooling2D object at 0x7f26c86e6c88>	block1_pool	False
4	<keras.layers.convolutional.Conv2D object at 0x7f26c867dc18>	block2_conv1	False
5	<keras.layers.convolutional.Conv2D object at 0x7f26c8690f28>	block2_conv2	False
6	<keras.layers.pooling.MaxPooling2D object at 0x7f26c869e5c0>	block2_pool	False
7	<keras.layers.convolutional.Conv2D object at 0x7f26c863f828>	block3_conv1	False
8	<keras.layers.convolutional.Conv2D object at 0x7f26c863f128>	block3_conv2	False
9	<keras.layers.convolutional.Conv2D object at 0x7f26c86607b8>	block3_conv3	False
10	<keras.layers.pooling.MaxPooling2D object at 0x7f26c83d7d68>	block3_pool	False
11	<keras.layers.convolutional.Conv2D object at 0x7f26c83fd358>	block4_conv1	True
12	<keras.layers.convolutional.Conv2D object at 0x7f26c83fddd8>	block4_conv2	True
13	<keras.layers.convolutional.Conv2D object at 0x7f26c839da20>	block4_conv3	True
14	<keras.layers.pooling.MaxPooling2D object at 0x7f26c83ac1d0>	block4_pool	True
15	<keras.layers.convolutional.Conv2D object at 0x7f26c834e978>	block5_conv1	True
16	<keras.layers.convolutional.Conv2D object at 0x7f271a15eb38>	block5_conv2	True
17	<keras.layers.convolutional.Conv2D object at 0x7f26c8371d68>	block5_conv3	True
18	<keras.layers.pooling.MaxPooling2D object at 0x7f26c8314b00>	block5_pool	True
19	<keras.layers.core.Flatten object at 0x7f26c828bda0>	flatten_1	True

Figure 37: Illustration of Unfrozen Layers for Fine-tuning

4.4. Evaluation Results

4.4.1. Random Test Images Classification

Choose random images from test dataset. The image can be either 'NORMAL' or 'PNEUMONIA'. Classify the image using the pre-trained models and plot the image with its actual label and predicted label. Figure 38 describes the random generation of test images and their classification using the VGG16 model with Image Augmentation and Fine-Tuning method.

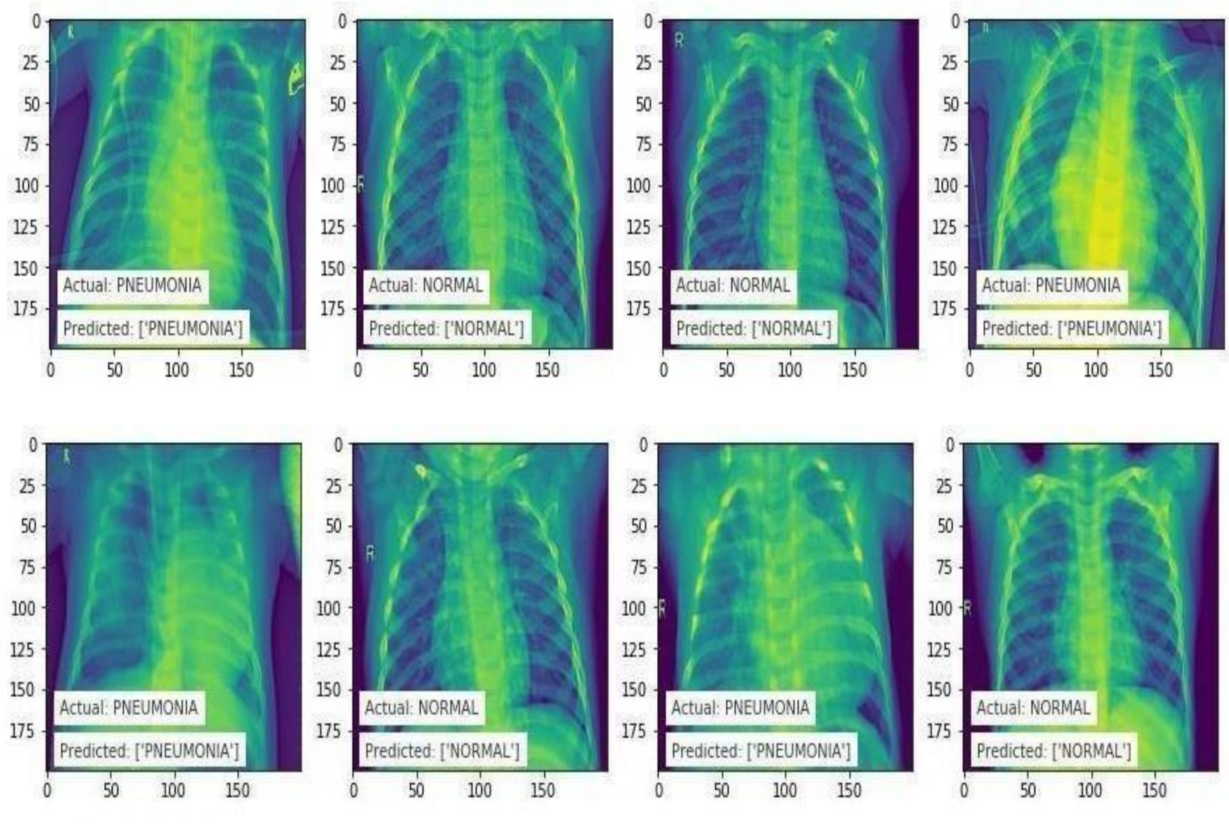


Figure 38: Classified Images

4.4.2. Accuracy

The prediction accuracies of all pre-trained networks with the corresponding method of the classification is listed in Table 5. From the three approaches used, Feature Extraction with Image Augmentation gave the best results, out of which the 'Xception' model achieved the best accuracy with 92.5%. Figure 39 shows the bar plot visual of all accuracies.

Table 5: Accuracy Results

Model	Conv Method	Image Augm	Fine Tuning
VGG16	84.75	92.15	87.17
VGG19	76.118	91.42	88.52
ResNet50	79.82	90.11	63.17
InceptionV3	78.217	88.521	68.04
Xception	83.594	92.57	67.46
DenseNet	81.56	88.98	56.66

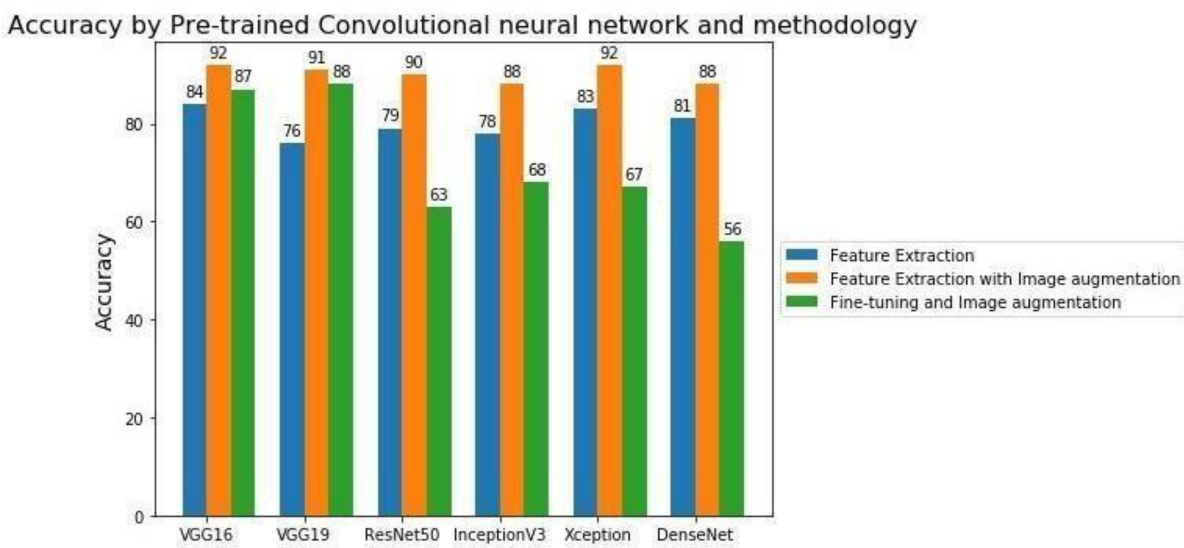


Figure 39: Bar plot of Accuracy Values Obtained

4.4.3. Precision

As Precision describes the true Pneumonia images out of predicted Pneumonia, Table 6 and Figure 40 represents the percentage measures of the same. From the three approaches, the Feature Extraction with Image Augmentation gave the best results, out of which the 'VGG16' model achieved the best precision value of 94.55%. Figure 40 shows the bar plot visual of all the precision.

Table 6: Precision Results

Model	Conv Method	Image Augm	Fine Tuning
VGG16	90.66	94.559	90.45
VGG19	84.16	93.5	94.1
ResNet50	89.68	93.42	76.07
InceptionV3	85.26	90.95	80.16
Xception	89.7	94.11	81.57
DenseNet	88.28	92.4	77.16

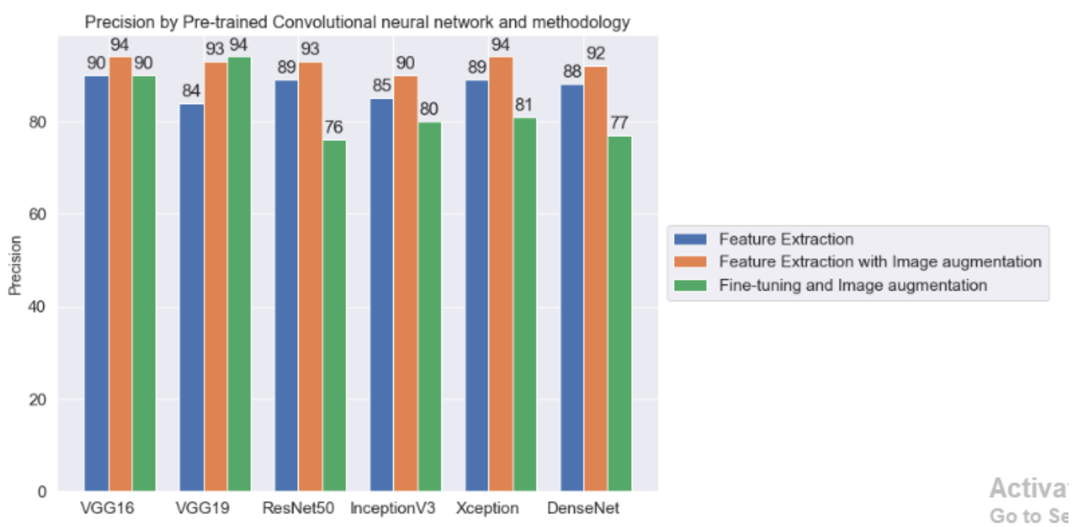


Figure 40: Bar Plot of Precision

4.4.4. Recall/Sensitivity

As Sensitivity is the probability of being tested positive when the disease is present, Table 7 and Figure 41 represents the results of the test to correctly classify an individual as 'diseased'. From the three approaches used in this paper, Feature Extraction with Image Augmentation gave the best results, out of which the 'Xception' model achieved the best Sensitivity of 94.35%.

Table 7: Recall/Sensitivity Results

Model	Conv Method	Image Augm	Fine Tuning
VGG16	87.17	93.58	87.43
VGG19	81.79	92.3	90
ResNet50	80.25	91.02	73.06
InceptionV3	83.07	90.25	76.66
Xception	87.17	94.35	77.17
DenseNet	88.07	90.51	75.38

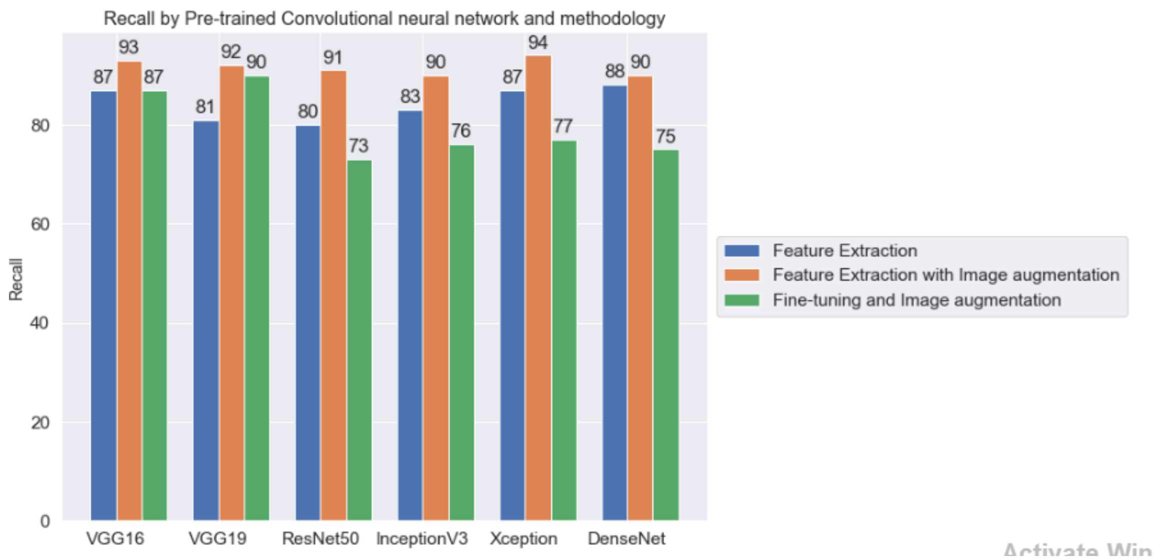


Figure 41: Bar Plot of Sensitivity

4.4.5. Specificity

As Specificity is the probability of being tested negative when the disease is not present, Table 8 and Figure 42 represents the results of the test to correctly classify an individual as 'not diseased'. From the three approaches used, Feature Extraction with Image Augmentation gave the best results, out of which the 'VGG16' model achieved the best Specificity of 93%.

Table 8: Specificity Results

Model	Conv Method	Image Augm	Fine Tuning
VGG16	88.33	93	88
VGG19	80	91.66	92.66
ResNet50	88	91.66	71
InceptionV3	81.33	88.33	75.33
Xception	87	92.33	77.33
DenseNet	85.66	90.33	71

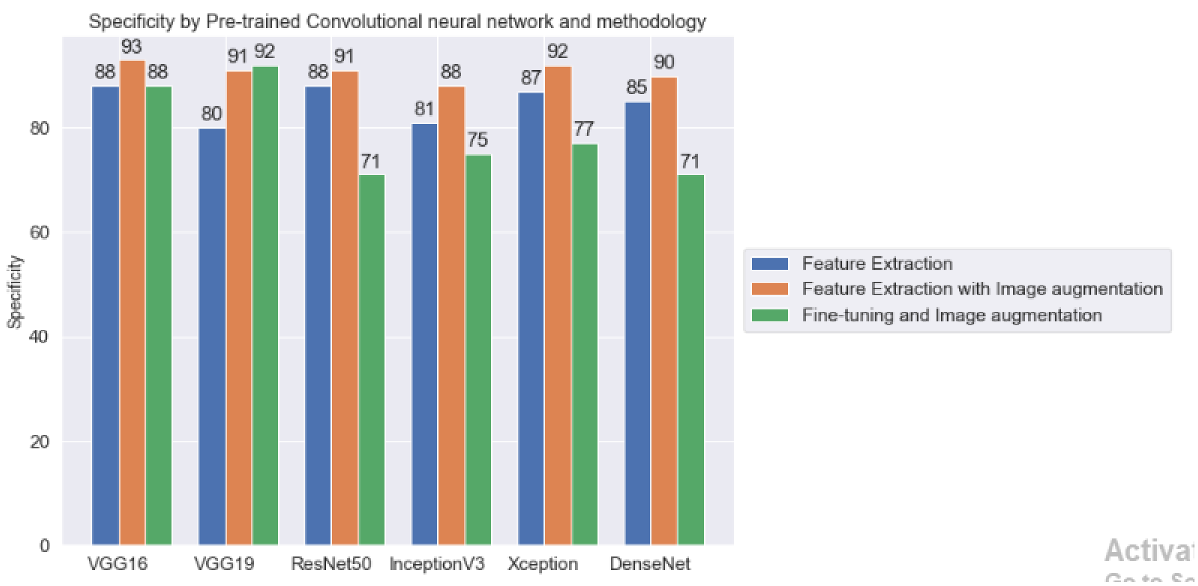


Figure 42: Bar Plot of Specificity

4.4.6. F1-score

As the dataset classes distribution are unbalanced, the F-1 score shows the better accuracy values compared to normal accuracy measured. From the three approaches used in this paper, Feature Extraction with Image Augmentation gave the best results, out of which the 'VGG16' model achieved the best F1-Score of 94%. Table 9 and Figure 43 shows the DataFrame and Bar plot visual of F1-scores.

Table 9: F1-Score Results

Model	Conv Method	Image Augm	Fine Tuning
VGG16	88.33	94	88
VGG19	82	92.66	92.66
ResNet50	84	92.66	74
InceptionV3	84.33	90.33	78.33
Xception	88	93.75	79.33
DenseNet	85.66	91.33	76

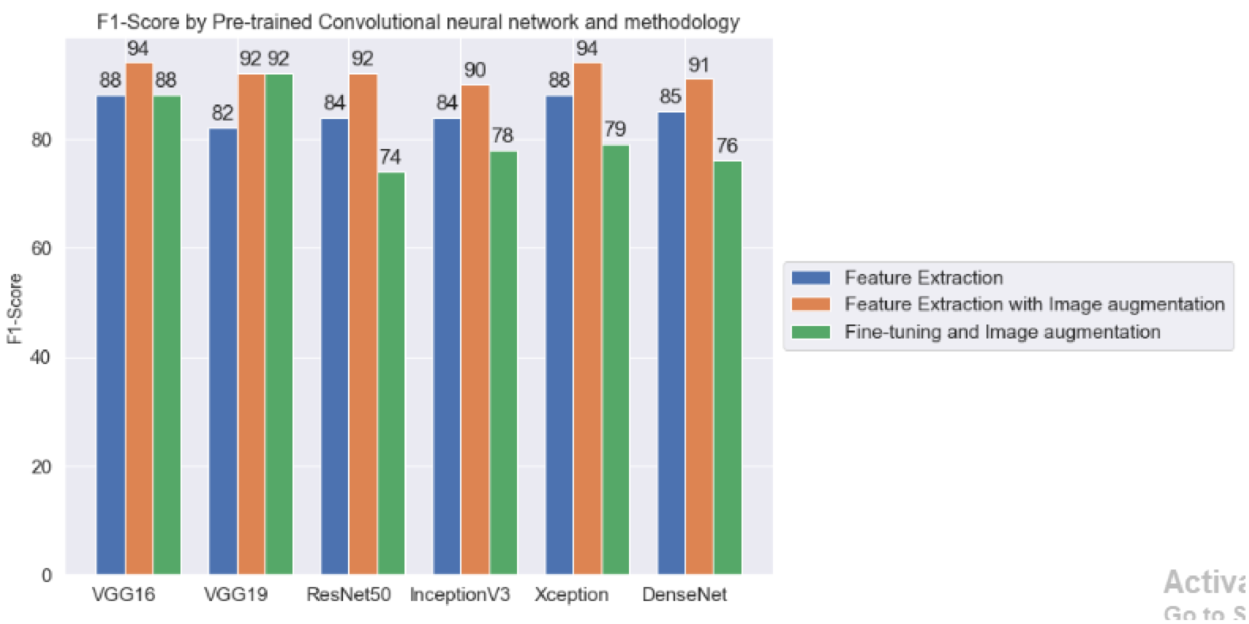


Figure 43: Bar Plot of F1-Score

4.4.7. Confusion Matrix to Show True Normal and True Pneumonia

Majority of True Normal and True Pneumonia are classified well in all cases. Normal is indicated by '0' and Pneumonia is indicated by '1'. As the Feature Extraction with Image Augmentation achieved best results, Figure 44 shows confusion matrices of that approach [31].

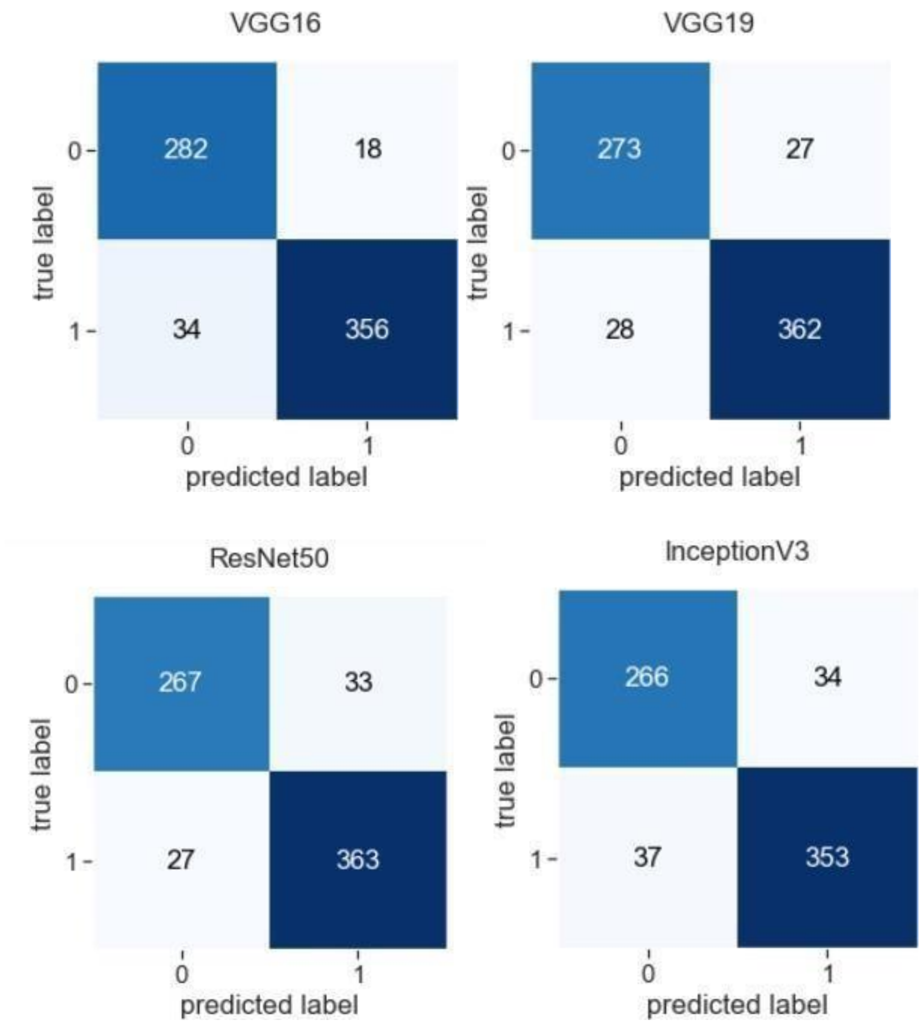


Figure 44: Confusion Matrices of All Models

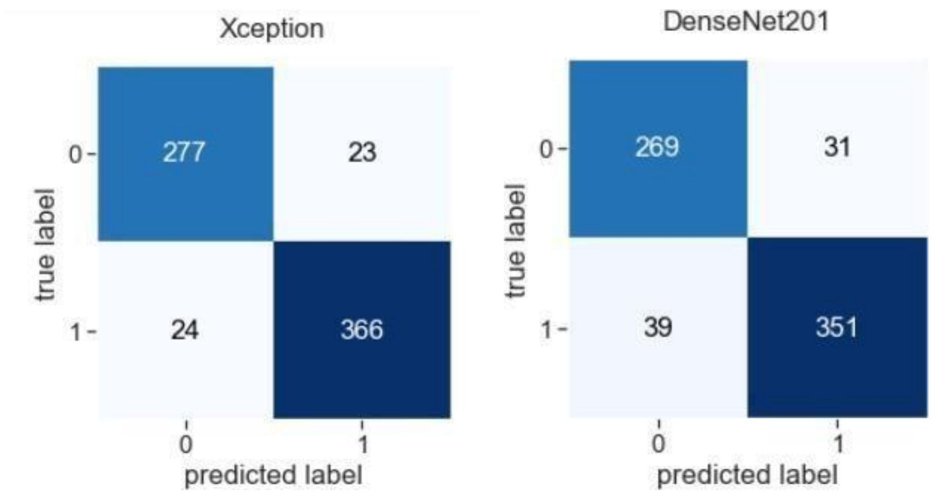


Figure 44: Confusion Matrices of All Models (continued)

4.4.8. ROC Curve for Best and Worst Model

Figure 45 describes the Receiving Operating Characteristic curve for the best and worst models, respectively [32].

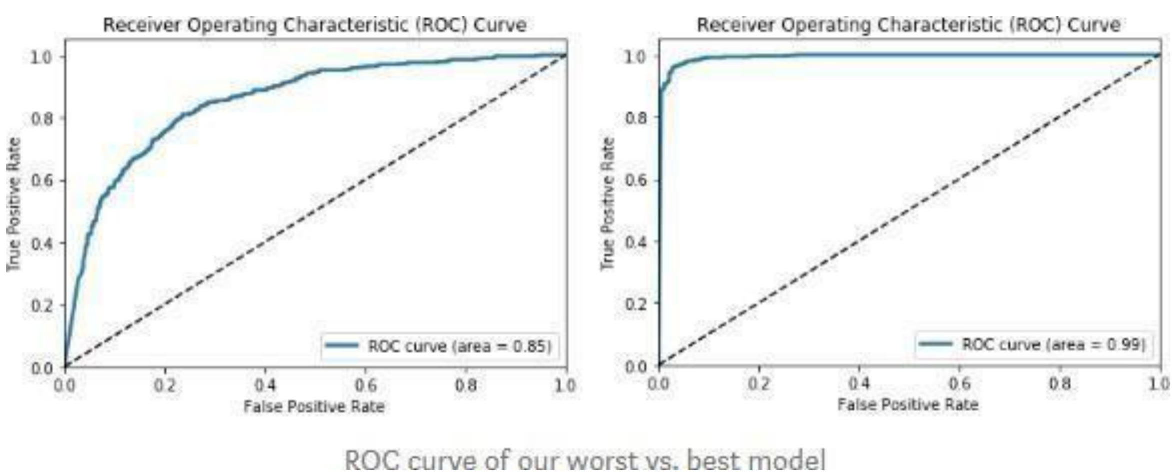


Figure 45: ROC Curve

5. CONCLUSION

The project work compares the performance of six pre-trained convolutional neural networks with three types of approaches, namely CNN as feature extraction, CNN as feature extraction with image augmentation, and CNN with fine-tuning and image augmentation. The dataset includes chest X-rays of Normal and Pneumonia patients.

With the help of transfer learning and the approaches mentioned above, better accuracy values are achieved with almost all the pre-trained networks for the classification of medical images. In all the pre-trained networks used, Feature extraction with Image augmentation method delivered the best results. Of all the networks the ‘Xception’ model with Image Augmentation as feature extraction method returned the highest accuracy of 92.5% followed by VGG16, VGG19, ResNet 50, InceptionV3 and DenseNet201 with 92.1%, 91.42%, 90%, 88% and 88%, respectively. The same method showed better indication in terms of Sensitivity where as the ‘VGG16’ model showed better results in specificity, precision, recall and F1 score. Hence, when the datasets are balanced and unbalanced, the Feature Extraction with Image Augmentation approach with the pre-trained networks ‘Xception’ and ‘VGG16’ performed well respectively.

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