Analysis of Chest X-Ray Images and Detection of Pneumonia Using Deep Learning

Varsha Dange, Varun Patil, Shreya Pawar, Yukta Pedhavi, Parikshit Pohane and Pranita Maske

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Varsha Dange [1] ,Varun Patil [2] ,Sherya Pawar [3] Yukta Pedhavi [4] Parikshit Pohane [5] Pranita Maske [6]

[1, 2, 3,4,5,6], *Vishwakarma Institute of Technology, Pune, Maharashtra, India*
[a)] *dange.varshar@gmail.com*
[b)] *varun.patil20@vit.edu*
[c)] *shreya.pawar20@vit.edu*
[d)] *yukta.pedhavi20@vit.edu*
[e)] *parikshit.pohane20@vit.edu*
[f)] *pranita.maske20@vit.edu*

Abstract. On account of pneumonia, the lungs are impacted by a bacterial contamination. An early examination is critical to a successful cure. In most cases, an expert radiologist can determine the dilemma with a chest X-ray. The visualization can be self-endorsing for a spread of reasons, for example, a strange look on the chest X-beam photographs or perhaps muddled with different sicknesses. As a result of this, practitioners will need to be guided by computer-aided diagnosing tools. The models Convolutional Neural Networks, VGG16 and Inception -V3 wear utilized in this research study were deep rooted for diagnosing pneumonia. Investigating results showed that the Vgg16 and Inception-V3 models were having an accuracy of 0.80%, and 0.76% individually. However, when compared to the Inception-V3 model, the Vgg16 model proven more effective in detecting pneumonia patients. This study demonstrates that each model has its own specialty and capabilities for the same dataset.

Keywords: Pneumonia detection, transfer learning, convolutional neural networks, Inception V3, VGG 16; deep learning, Chest X-ray.

1 INTRODUCTION

Pneumonia is caused by a bacterial infection that provokes tissue inflammation in one or both lungs. Every year, more than 1 million people in the United States are hospitalized due to pneumonia. Unfortunately, this illness has taken the lives of 50.000 people [1]. Thankfully, antibiotics and antiviral can be used to treat pneumonia. Early recognition and diagnosis of pneumonia, on the other hand, is critical in order to avoid serious complications that could result in death [2]. Chest X-ray images are the most well-known and extensively utilized clinical technique for diagnosing pneumonia [3].

Even experienced radiologists found difficulty for diagnosing pneumonia from chest X-ray images. On X-ray images, pneumonia appears vague, and It can be confused with other diseases or function as a number of other mild abnormalities. Because of these discrepancies, there were many subjective judgments and variances in pneumonia diagnosis among radiologists [4-6]. As a result, radiologists will require electronic aids to assist them in identifying pneumonia by analyzing chest X-ray images.

Deep learning advancement, in particular convolutional neural networks (CNNs), has demonstrated pervasive potential in photo categorization [7]. The ultimate focus of CNNs is to build an artificial version that strongly resembles the visible cortices of the human brain. CNNs have the advantage over handcrafted features in that they can extract more significant properties from the entire image [7, 8]. The researchers created a set of deep networks based on CNN that produced leading-edge results in computer vision classification, segmentation, object detection, and localization [9-11].

But apart from natural PC vision problems, CNNs have demonstrated clinical potential in breast cancer identification [12], brain tumour segmentation [13], Alzheimer's disease analysis [14, 15], and skin lesion categorization [14, 15]. Here are some of the best deep learning perspectives on clinical image processing [16, 17]. In terms of findings, even a few studies have used deep learning to diagnose pneumonia. In year 2017, Antin et al. achieved 0.60 percent area under the curve (AUC) using a DenseNet-121 layer and the exchange inclining method [18].

Rajpurkar et al. published CheXNet [20], a 121-layer convolutional neural network built on DenseNet [19], in 2017. They used 10.000 front facing view chest X-beam photos with 14 different disorders to prepare their organization. Four expert radiologists investigated the organization's exhibition by using f1 score metric. CheXNet received a score of 0.435 (95 percent confidence interval [CI] 0.387, 0.481), which was more than the radiologist average of 0.387. (95 percent CI 0.330,0.442).

Based on this knowledge, the author modified and founded two well-known organizations for diagnosing pneumonia from chest X-ray images. The Xception model [21] serves as the foundation of our organization. Vgg16 [22] is used in the following model. This model also made use of approaches such as move learning, calibration, and data expansion. This proposal has used similar limits to ensure an objective correlation when preparing the two organizations. This approach, too, used various variables to examine the presentation of two companies based on test data. The Xception model outperforms the Vgg16 model when it comes to pneumonia analysis. The Vgg16 model, on the other hand, did a better job of diagnosing common cases.

1.1 Motivation

Chest X-ray, Computed tomography of the lungs, chests ultrasound, plus MRI of the chests [2] should all be done to diagnose pneumonia. X-rays are now one of the most efficient diagnostic techniques for pneumonia [3]. Detecting pneumonia on X-ray films is a intricate task that necessitates the participation of a team of experts. As a result, analyzing an X-ray for pneumonia can be time-consuming and incorrect. The implication is that disease like lung cancer, high blood pressure, specific diseases X-ray imaging and fuzzy vision symptoms, are all similar to a variety of other uncertain disorders. As a result, accurate X-ray readings are essential.

1.2 Medical Care

Pneumonia is a one type of infected disease that affects inflammation of the air sacs in one or even lungs. The air sacs can become clogged with liquid or discharge (purulent material), causing a mucus-filled hack, diarrhea, nausea, shivers, and inability to relax. The diverse range of living things, including microbes. Pneumonia is caused by an infection and growths. The prototype is qualified to diagnose patients who fall into one of two categories: He/she has a positive or negative attitude.

A. Positive Patients:

Those patients who are suffering from the pneumonia disease falls under this category as shown in Fig.1(a).

B. Negative Patients:

Those patients are not suffering from the pneumonia disease falls under this category as shown in Fig.1(b).

	
Figure 1 (a)- Positive Patient	Figure 1(b) - Negative Patient

2 Literature Survey

Puneet Gupta suggested a model for detecting pneumonia utilizing a variety of preprocessing and CNN settings, data augmentation approaches, and supplementary X-ray datasets with more details on various diseases, which will be investigated further in future study. [1]

In this work, Okeke Stephen, Uchenna Joseph Maduh, Mangal Sain, and Do-Un Jeongthe pneumonia tuned and prepared many CNN architectures to create a model. The project also aims to reduce the size and purpose of the images used, while still altering the model's display. [2]

Deep learning was utilized by Mohammad Farukh Hashmi, et al. to recognize pneumonia. 1000 preparation ages were used to build the Deep Convolutional Neural Network using the NVidia Tesla v100 GPU and TensorFlow structure. [3]

Enes AYAN and Halil Murat ÜNVER use the convolutional neural network models Xception and the concept of VGG16 to diagnose pneumonia in their work. They used deep transfer learning and fine-tuning during the training stage. [4]

The given document was proposed by Dejun Zhang, Fuquan Ren, Yushuang Li, Lei Na, and Yue Ma for detection. In order to assist healthcare practitioners, This study designed an automated CAD framework that uses profound exchange learning-based classification to divide chest X-ray images into two categories: pneumonia and normal. A group system was developed that takes the choice scores from three CNN models, GoogLeNet, ResNet-18, and DenseNet-121, to create a weighted typical outfit. [5]

Tatiana Gabruseva and et al. used a convolutional neural network approach that was get trained from scratch to detect and classify the presence of pneumonia. They used a variety of data augmentation strategies for improvement in the CNN model's, validation and classification accuracy, and the results were impressive. [6].

A different convolutional brain network model was used in the paper by V. Sirish Kaushik, Anand Nayyar, Gaurav Kataria, and Rachna Jain, they have used 4 convolutional layers are used in the first, second, third, and fourth models, respectively. Dropout regularization concept has been used to prevent over fitting. [7]

In Emrah Irmak's review, two convolutional neural network models are provided for two distinct grouping assignments utilizing publically accessible information sets, the first of which recognizes COVID-19 and the second of which isolates them into three classes: COVID-19, ordinary, and pneumonia. The Grid Search Optimizer approach is used to resolve hyper parameters. [8]

Simple VGG-based model architecture with few layers was created by Dejun Zhang, Fuquan Ren, Yushuang Li, Lei Na 2 and Yue Ma. The Dynamic Histogram Enhancement approach is used to pre-process the pictures to address the lack of contrast in chest X-ray images, which leads to ambiguous diagnosis. [9]

Mohammad Farukh Hashmi, and et al. present a classifier-based methodology that best blends the demands of cutting-edge profound learning models like ResNet18, exemption, InceptionV3, DenseNet121, and MobileNetV3. Incomplete information expansion procedures are employed to appropriately generate the preparation dataset. [10]

In this study, Enes Ayan and Halil Murat Ünver focused on two CNN models, Xception and Vgg16, for diagnose pneumonia. They trained the model based on concept of transfer learning and fine-tuning. They compared two network test results after training. [11]

Dimpy Varshni, and et al. assessed the features and functions of previously trained CNN models used for feature extraction and then classifiers use it to classify it as anomalous or normal X-rays. [12]

A new method for detection is presented by Hanumant Magar, and et al. They employed the CNN method. They employed a convolutional neural network technique to produce feature maps of the preprocessed X-ray images. [13]

Using deep CNN-based transfer learning approaches, this paper presented an adaptive diagnosis of pneumonia in X-ray scans. This system was presented by Amit Ranjan (B), and et al. The suggested model was trained using 5856 chest X-Ray images (4273 scans of pneumonia class and 1583 scans of normal class). To evaluate the model, the authors used accuracy, precision, recall, and f1 score measurements, as well as a public experiment. [14]

3 METHODOLOGY

3.1 Proposed Data model architecture:

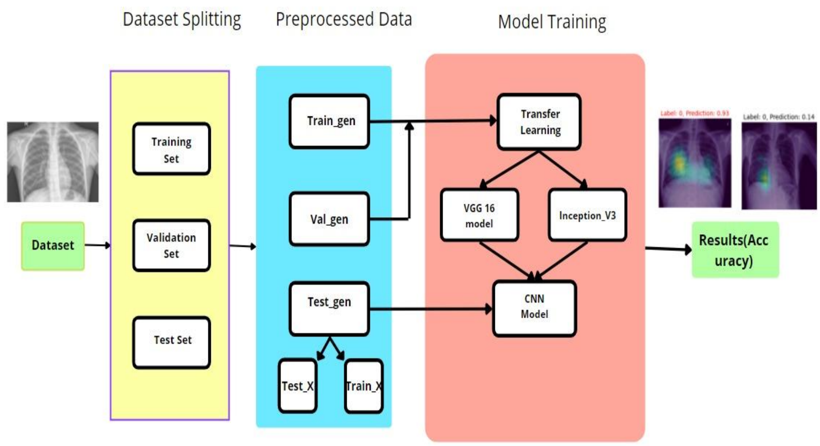

Fig. 2.- Model Architecture for proposed system

3.2 Dataset

The Dataset of NIH Chest X-ray includes 1, 12,120 X-Ray films of disease , from which proposed system uses 30,805 unique patients match data . The dataset in .csv file format is pre-present in the dataset that comprises of images Index, labels, Id, Age, gender of patients and width and height of Images.

3.3 Data Preprocessing

All transformations performed on raw data prior to feeding it to the machine learning or deep learning algorithm is referred to as pre-processing. Technically Data preprocessing is a technique in which the main aim is to transform the data into that form which is compatible for the model to understand

Before data can be used, it must be preprocessed. The transformation of raw data into a clean data set is the theory of data preprocessing. The dataset is preprocessed before applying the algorithm to check for missing values, noisy data, and other inconsistencies.

In this proposed model, firstly the dataset is imported and split into three parts train, test and validation. Now each train, test and validation set is been initialized. After that now this set will be need to transform into proper form of images using ImageDataGenerator which comprises of attributes like (range of height shift, rescale of image, flip the image horizontally and vertcally ,range of width shift, range of rotation, range of shear, range of zooming, mode of fill, brightness). The ImageDataGenerator will automatically label all the data inside folder as pneumonia which images are of positive patients and vis-a-vis for negative patients. By this function the model is the stage that the object of the class ImageDataGenerator is been created now for creating Data-frames of train-data and validation-data, pass each train-data and validation-data to data-frame attribute in the function which will convert the images into array which comprises of three values(RGB values for the particular image). So now as the data frame has been generated that will be passed into the model training.

3.4 Deep Learning Techniques

Convolutional Neural Network (CNN) Model:

Convolutional neural networks are algorithms that detect patterns in data. In general, neural networks are composed of layers of neurons, each with its own set of learnable weights and biases.

Convolution is a mathematical procedure that produces a third function that expresses how one function affects the shape of another. Throughout the forward pass, each filter performs a convolution procedure on the filter input, computing the dot product between the filter entries and the input and producing an n-dimensional output of the filter. As a matter of fact, the network applies filters that initiate when a special type of feature is detected in a particular spatial location in the input. Convolution is a mathematical inherent feature that determines the number of overlap between two functions g and f as they are transitioned over one another:

$c = (f * g)(t) = \text{(0 to t)} f(\tau) g(t - \tau) d \ldots [28]$

where:

c: convolution output function

f: original input function

g: function that is shifted over the input function

τ: shifting against t

VGG 16:

The VGG-16 network comprises 16 convolution layers and a 3x3 receptive field. There are 5 such levels, each with a Max pooling layer of size 2x2. Three fully linked layers follow the final Max pooling layer. Three fully connected layers are then added. As a final layer, it employs the softmax classifier. All hidden layers have their ReLu activated. The VGG16 model has the disadvantage of being burdensome to evaluate and necessitating a large amount of memory and parameters.

VGG16 has nearly 138 million parameters. The majority of these parameters (about 123 million) are in fully-connected layers, which are replaced in our model by an SVM classifier, reducing the number of required parameters significantly.

Inception V3:

Inception V3 is a CNN-based Deep transfer learning approach, was released by Google Net in 2014. This model has 42 layers and is less error-prone than its predecessors. It has 7x7 convolutions and uses an auxiliary classifier to spread label information throughout the network. It employs RMPS optimizers and includes label smoothing, a normalizing component added to the loss formula to prevent outliers in a class from causing over fitting in the model that produces the best results.

3.5 Important Parameters:

Rectified linear activation function (ReLU):

The rectified linear activation function (ReLU) is a simple linear or non-linear function which outputs the input directly based on positive or zero. otherwise. It's the most frequent activation function in neural networks, particularly Convolutional Neural Networks (CNNs) and Multilayer Perceptrons.Fig.3 shows graph for ReLU.

It can be stated mathematically as:

$F(x) = \max(0, x)$…[28]

It is represented graphically as,

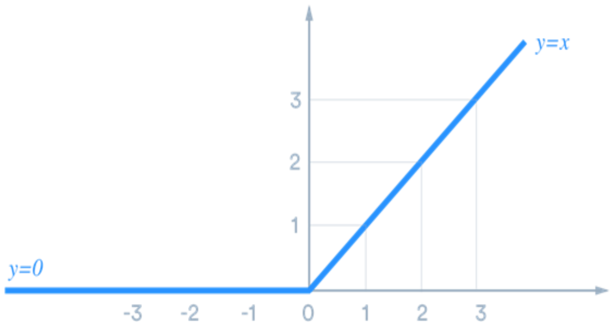

Fig.3 - Graph for ReLU[28]

The non-linear transformation of the data is achieved via ReLU.

Transfer Learning:

Transfer learning is a methodology which enables you to reuse the early stages of a model on a different methodology.

In this cycle, pre-prepared models are used as the beginning for arrangement, and not preparing by and by with haphazardly introduced loads. These models are prepared on exceptionally huge datasets yet this model can likewise utilize them on more modest datasets by performing information increase.

The exchange learning procedure entails preparing the CNN model on the large dataset using a basic organizational structure.. This prepared model result is commonly perceived as a previously-prepared model [20]. The learned highlights from its primary level are then transferred to the second dataset to be prepared. In this loop, the model uses a previously-trained VGG16 model trained on a dataset comparable to the current dataset to differentiate various leveled elements from a massive standard dataset.

Adam :

For Compiling the model Adam optimiser is generally used. Adam optimiser helps us to get out of local minima and reach global minima. So now the learning rate of the optimiser, here in our case is 3e-3. If the training is bouncing a lot in epochs then the model's learning rate must be decreased so that global minima can be achieved

Model Architecture:

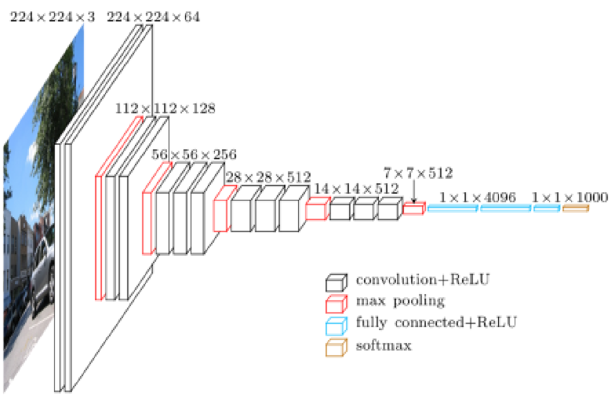

Figure 4 - Layers in Model[29]

Convolutional layers:

As shown in fig.4 ,In a convolutional neural network, applying learned filters to input images for creation of feature maps that illustrate the presence of those features in the input.

Maximum Pooling: Determine the highest value for each feature map patch.
A pooling layer is an additional layer that is added after the convolutional layer. After a nonlinearity, retrieve the feature maps produced by a convolutional layer. The pooling layer generates a new set of the same number of pooled feature maps by working separately on each feature map. When using a pooling layer, the length of each feature map is always reduced by a factor of two.

Fully Connected Layer:

The output of final Pooling is compressed and fed into the fully connected layer as the input. And after the fully connected layers applies the softmax activation function (rather than ReLU) to determine the likelihood of the input belonging to a specific class (classification).

Softmax:

Function Softmax is typically used at the last layer of a neural network to determine the probability distribution of an event over 'n' number of different events. The main advantage of the function is its able to handle different classes. Softmax's outputs are linked. The Softmax probabilities are always designed to add up to one.

Flow-Chart:

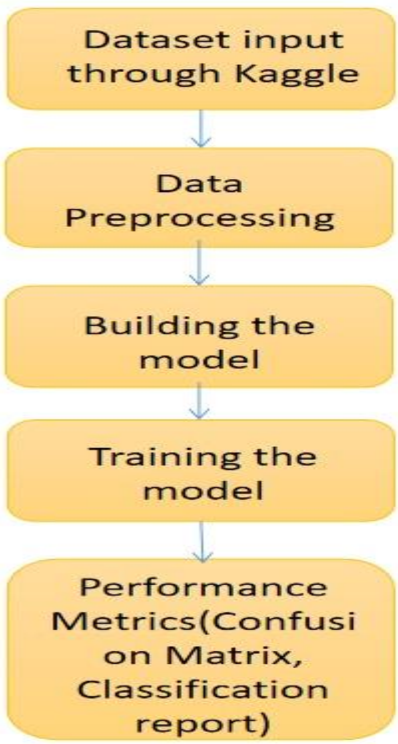

Fig 5 .Flow-Chart of proposed model

3.6 Performance measurement:

Confusion Matrix :

For binary classification, Confusion Matrix having the matrix of size 2×2 with the actual values on one axis and the predicted values on the other.

Table 1 - Confusion Matrix

	Negative	Positive
Negative	276	103
Positvie	37	49

True Positive (TP) – model predicts the positive class accurately (prediction and actual both are positive). The model predicts positively 49 patients with Pneumonia in the proposed model.
True Negative (TN) — predicts the negative class accurately (prediction and actual both are negative).
The proposed model predicts negatively for 276 people who do not have Pneumonia.
False Positive (FP) — the model predicts the negative class incorrectly (predicted-positive, actual-negative).
Although they do not have Pneumonia, 37 people are predicted to have it based on the proposed model
False Negative (FN)-Model predicts the positive class incorrectly (predicted-negative, actual-positive) in False Negative (FN).
The proposed model predicts that 103 people with Pneumonia will have a negative outcome.

Accuracy:

The accuracy is calculated by dividing the number of precisely classified data instances by the total number of data instances. In this study, the equation (1) largely shows how many times the model was true out of all the predictions it made.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TN} + \text{FN} + \text{FP}} \ldots \ldots (1)$$

Precision :

As per Equation (2), Precision demonstrates what percentage of all positive predictions is actually positive.

Precision $= \frac{\text{TP}}{\text{TP+FP}}$ …..(2)

The precision value ranges from 0 to 1.

Recall :

As per Equation (3) ,Recall displays what proportion of the total positive is projected to be positive.

Recall $= \frac{\text{TP}}{\text{TP+FN}}$ …..(3)

F1 Score :

There is a harmonic mean for precision and recall. It takes into account both false positives and false negatives. As a result, it does well with an unbalanced dataset.

F1 Score $= \frac{2*(\text{Precision}*\text{Recall})}{(\text{Precision}*\text{Recall})}$ ....(4)

Recall and precision are given equal weighting in the F1 score.

4 Results And Discussions

The resultant graphs for proposed model as shown in fig 7(a) and b for VGG 16 nd Fig.8(a) and b for Inception V3.

4.1 Vgg16 Model :

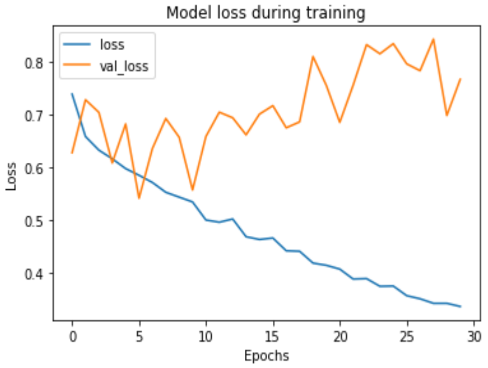

Fig.6.(a)Loss Curve for VGG-16 Model

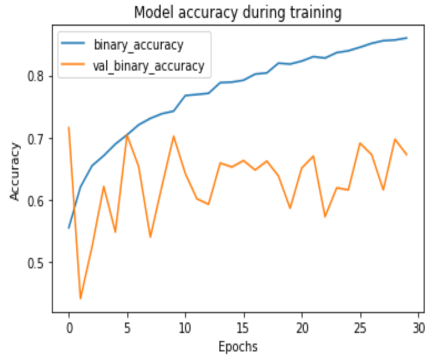

Fig.6.(b) Accuracy Curve for VGG-16 Model

4.2 Inception-V3 Model:

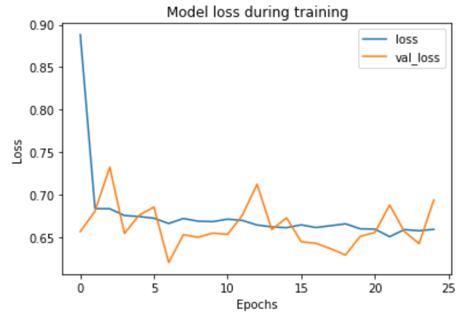

Fig.7.(a)Loss Curve for Inception-V3 Model

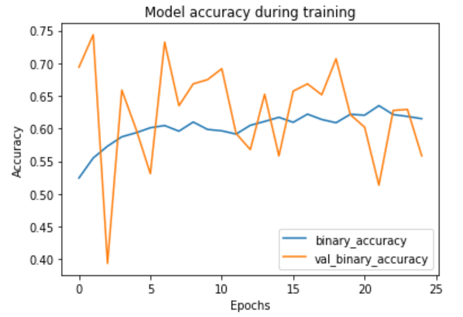

Fig.7.(a) Accuracy Curve for Inception-V3 Mode

The Table 2 below shows the Classification report of both the model which are performed in the proposed paper

Table 2 - Accuracy Comparison Table between VGG-16 and Inception-V3

TF Model	VGG-16		Inception-V3	
	No Pneumo-nia	Pneumonia	No Pneumonia	Pneumonia
Accuracy	0.80		0.76	
Precision	0.88	0.32	0.92	0.24
Recall	0.73	0.57	0.41	0.84
F-1 Score	0.80	0.41	0.57	0.38

The Graph shown in fig.9 given below the actual comparison of classification report of both the models-VGG16 and Inception V3.

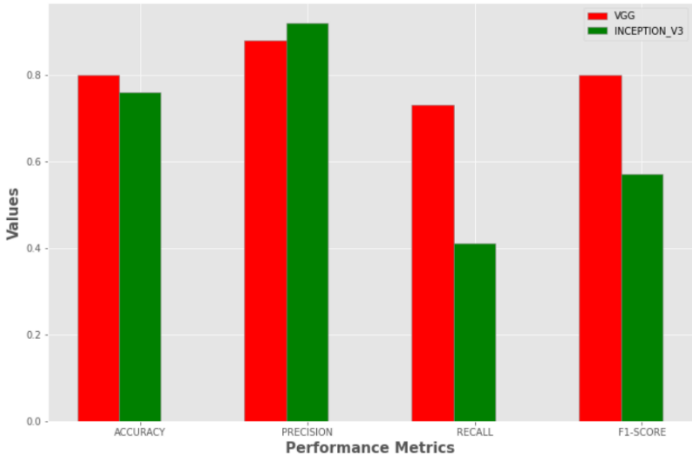

Fig8.– classification report chart for the models-VGG16 and Inception V3.

5 CONCLUSION

Deep Learning approaches are unique ways for detecting and classifying distinct anomalies in eye pictures, and they have a lot of promise for diagnosing ocular diseases efficiently. To perform automatic feature extraction that helps medical decision making, these algorithms take advantage of a wide number of accessible datasets with various annotations of clinical symptoms and ocular illnesses.

As from the technical background the Vgg16 model has more accuracy than the Inception-V3 model.

As a future scope to this research, with aim is to increase the model accuracy by collecting more data and improve the model architecture by ensemble techniques aiming to reduce the percentage of false negative errors in the model. This technique could be expanded in the future to detect and discriminate multi-elegance X-ray images. Furthermore, the efficiency of biomedical image segmentation could be improved by using more advanced function extraction algorithms based entirely on recently discovered deep learning styles.

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