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MCBM: IMPLEMENTATION OF MULTICLASS AND TRANSFER LEARNING ALGORITHM BASED ON DEEP LEARNING MODEL FOR EARLY DETECTION OF DIABETIC RETINOPATHY

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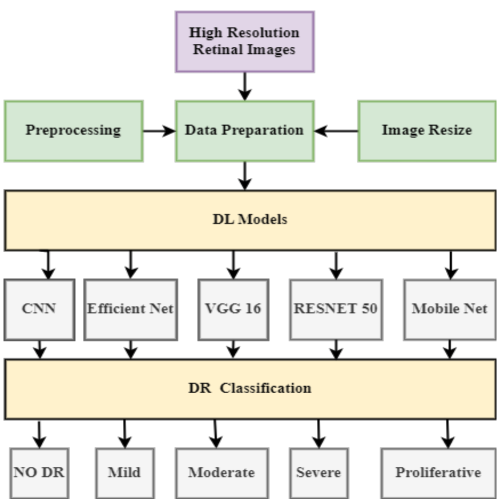
Graphical abstract



Abstract

Diabetic retinopathy (DR), the primary cause of a visible disease in working-age adults, is often controlled with the aid of early detection to prevent sight loss. This research proposes a collection of automated deep-learning techniques for DR screening. In this paper, we collected total 3662 Images from the Kaggle. Out of the total 3662 images, 90% (3295) images taken for the training purpose and 10% (367) for the testing purpose. This study measured the performance and comparative study of five Deep Learning models such as CNN, Efficient Net, VGG 16, Mobile Net, and RESNET 50 are demonstrated to improve the accuracy by changing various parameters of these models to classify DR in different stages. Out of the total images. Our finding shows that Efficient Net achieved a training accuracy of 0.9342 and a testing accuracy is 0.8181 and RESNET 50 achieved 0.9329 accuracies for the train data set and the test data set with 0.8116 accuracies. Efficient Net and Res Net 50 have achieved better accuracy out of the five models. Hence these two models perform well as compared to the other 3 Models.

Keywords: Diabetic Retinopathy, Deep Learning, Convolution neural network, Efficient-Net.

1.0 INTRODUCTION

Eye sightlessness is a severe disease that affects everyone. Diabetic Retinopathy (DR) and Glaucoma are two common causes of vision loss. Deep learning is being used in medicine to anatomically form retinal images and conduct execution is divided into the context of eye disorders such as Diabetic Retinopathy, and age-related degeneration. For the time being, artificial intelligence based on Deep Learning calculations is being used for eye recognition diseases. Because of polygenic conditions, excess blood glucose causes diabetic retinopathy. Over time, too much sugar in the blood will damage the tissue layer, which detects light and transmits messages to the brain through a nerve at the back of your neck (optic nerve). Diabetes causes damage to blood arteries throughout the body. Sugar restricts the small blood arteries that attend the tissue layer, causing them to leak fluid or bleed, resulting in damage to your eyes. To compensate for the clogged blood vessels, eyes generate new blood vessels that don't work properly. These newly formed blood vessels are about to explode. There is a lot of research on detecting lesions in the retina. Yehui Yang et al.[1] In fundus images, they presented a two-stage DCNN to detect suspicious lesions and DR severity classes. The efficiency has been demonstrated by the outcomes of the experiments. The proposed algorithm and this research can be quite useful in DR Examination information for clinical ophthalmologists.

Avula Benjamin et al. [15] The Tensorflow deep learning framework was used to create the deep learning model presented in this study. The deep learning model built in this study was used to detect hard exudates present in the DR DR-impacted due picture. The presented model has more than 90% accuracy in detecting hard exudates.

The structure of this research paper follows: Section 2 describes related work. Section 3 introduces the methodology and brief explanation of deep learning models for image classification, confusion matrix, CNN, Efficient Net, Resnet50, VGG 16, Mobile Net, and Basic steps. Section 4 describes the model performance in the Experimental results of various samples and briefly discusses the results, Section 5 concludes the paper.

2.0 RELATED WORK

Author Y. Luo et al. [2] taught that the SFCN is divided into three basic phases. To complete the longer-term learning module, a couple of unshapely convolutional layers were used in the first phase to remove CNN representations from the retinal picture and reconstruct the provided retinal picture using various deconvolutional layers. The second section used the predicted outcome of fuzzy bunching computation to control preparation. Finally, they figured out how to use the fully automated system to perform retinal image grouping.

Mike Voetset.al [3] re-used the primary procedure of JAMA 2016; 316(22), however, utilizing publicly available data, they were unable to get the same results as those reported in that article. The original study had access to higher-quality data than what is publicly available, which is likely to explain some of the discrepancies in results.

Jen HongTanet al.[4] Retinal lesions such as Exudates, hemorrhages, and micro-aneurysm segmentation is a difficult task. They created an algorithm that used a convolutional neural network of 10 layers to separate and classify exudates, hemorrhages, and micro-aneurysms automatically and simultaneously. Before being fed into the network, the input image was normalized. The CLEOPATRA database was used to train and test their technique.

Nitigya Sambyaletal.[5] This research developed a method for pixel-smart segmentation of retinal abnormalities such as microaneurysms and exudates. They used IDRiD and e-ophtha datasets, as well as a modified UNet structure with a pre-trained ResNet34 encoder. Exudates and microaneurysms are semantically segmented and extracted from the dataset's fundus pictures.

Andrzej Grzybowski1et al.[6] The use of artificial intelligence in Ophthalmology is fast developing. There have been several new screening technologies described in recent years, and have claimed strong results in detection. Only a few of these, however, are currently in use. It is available for purchase. AI-assisted detection of DR could be beneficial. Despite this, they play a vital role in the treatment of blindness.

Badar et al.[7] In this research, authors used Deep neural network versions such as GoogleNet, LSTM, AlexNet, and VggNet were studied in order to extract retinal structural components.

Lee et al. [8] VGG-16 is utilized for 3-D OCT. There is no paradigm for applying retinal image analysis with retinal photographs. These networks are all extremely complex. That has the capacity to extract far more complicated characteristics than older approaches and improved key metrics.

Yaxin Shenaet. Al [9] suggested a method that assesses the fundus picture quality by using quality factor analysis to forecast the overall quality task in terms of the field definition. Polar transformation, landmark localization, and domain adaptability are all part of the proposed architecture. The scaled aggregate of the image feature is used to examine the fundus pictures. They have also designed semi-tied domain adaptation for picture quality evaluation, which can increase approximation between the source and destination domains.

G. T. Zago et.al [10] this research aims to use a CNN deep network technique to detect DR in retinal pictures early. Their model uses patches to locate possible lesions, making it a useful tool for an expert in retinal red lesions and may result in more DRs. The primary objective was to simplify the model while also boosting its performance. To that purpose, they devised a method for picking training patches that would ensure that difficult instances received much interest during the training activity.

S. R. Sadda et.al [11] used a qualitative methodology in this work to assess the impact of the distinct impact of DR lesions across the fundus on the risk of PDR development. The frequency and surface area of intraretinal H/ma, as well as hemorrhages from the foveal or ONH center, appeared to be connected to a greater risk of advancement, according to their results.

Authors Amita Meshram, at.el[12] analyzed different DL Algorithms for the detection of DR. Balazs Harangi et al.[13] This research proposes an ensemble-based neural network architecture for recognizing MAs in fundus images. Their model connects various DCNNs to one another permitting their concurrent training to the variety of the population. The proposed architecture can respond thanks to the DCNNs that have been chosen. Thereby adopting more dynamically to the variety of fundus pictures improves categorization performance as expected.

Clément Playout et al. [14] They recommend for a multi-challenge learning enhancement to the U-Net architecture: rather than a single encoding module, more than one decoding module is employed for green categorization. They advocate encoding module enhancements based on recent CNN discoveries, residual connections in respect scales, huge kernels for bottom-scale convolutions, and mixed pooling for spatial compression.

Gazala Mushtaqet et.al [16] presented a detailed review of several approaches for automatically diagnosing diabetic retinopathy and they tried to offer their deep learning methodology for retinopathy clinical prediction utilizing a DenseNet169. They employed a regression model in addition to the DenseNet-169 classifier to compare the results.

Li, Fangjun, et al.[17] Their technique gives novel results in the assessment of Diabetic Retinopathy using the EyePACS dataset. Furthermore, behaviour systematic tests have an effect on image resolution, revealing that as the device evolves with increased entry image resolutions, total performance rises logarithmically, while each time and computation value climbs immensely.

S.Preetha et al.[18]. They may develop software to forecast diabetic patients using the Knowledge Base, which has a dataset of around 2000 diabetic cases, and make suggestions based on the presence of diabetes patients. Forecasting will be made using two Nave Bayes and K-Nearest Neighbor algorithms, and the success factors will be used to determine which approach delivers the best accuracy. The program that will be developed and utilized in the Healthcare Industry for the Therapy Monitoring of Patients.

Saivya Gulati et.al. [21] In their proposed method without human interference, CNN can detect features from images and

CNN can also be best for image classification. In this paper, the disadvantage of the proposed method is that, for better accuracy, it needs a large number of Images.

Feng Li et.al. [22] Proposed a method by which they gathered retinal pictures that were pre-screened for quality and other disorders by human graders. The generated high-quality retinal pictures formed the development dataset, which was utilized for model training and intra-dataset validation. But this less dataset was insufficient for better performance. So, the authors' future work will use a large number of the dataset for better performance to detect DR.

D. Siddharth et.al.[23]. In this research, they employed the Kalman Filter approach to create a one-of-a-kind filter, KFA+ANN, for edge identification in greyscale pictures. They used a basic image and its edge map to create a new filter in the approved method. Using the ANN approach, image localization accuracy was proved to improve in this work. Kalman filtering is used to ANN-acquired object coordinates. According to the findings, combining ANN with Kalman Filtering improv

es localization.

3.0 METHODOLOGY

3.1 Data Source

The information for this research was obtained from Kaggle's Diabetic Retinopathy Detection APTOS 2019 blindness detection[23]. 3662 retinal pictures under various situations are taken from datasets. And retinal images are divided into various categories shown in Table 1.

Table 1 Images are Divided into a Category

Image Category	Mild	Moderate	No DR	Proliferate	Severe	Total Images
Count	370	999	1805	193	295	3662

Split the dataset of 3662 images into the train dataset and test data set in the ratio of 3295:367.

The fact that those retinal images were captured using a variety of locations and equipment makes them noisy, which is undesirable. There seems to be something that has to be removed, which calls for several preprocessing steps. The retinopathy associated with each picture was graded for diabetes individuals on a scale of 0 to 4 as follows:

-No DR,1-Mild,2-Moderate,3-Severe,4-Proliferative

A retinal picture with a level of 0 indicates that there are no DR-related symptoms present.1-Low DR indicates that the retinal picture contains a variety of characteristics, including hemorrhages, hard exudates, and macular edema. 2-Medium DR value indicates the presence of extensive hemorrhages,3-high DR values suggest hemorrhages and 4-high DR values indicate pre-retinal hemorrhages [19]

3.2 Image Classification of Deep Learning Model

Making the process easier depends on this step. The photos are then metameric, which divides them into several groups. Following pre-processing, feature extraction is carried out, which involves the extraction of numerous options from the picture understanding, such as Optic Distance, vessel, carried out scientific Entropy Exudates space, and chemical assessment of these options. The extracted alternatives from the image are selected and categorised using a Deep Learning algorithmic program.

Convolution Neural Networks (CNN) and low-cost Internet are being used increasingly in deep learning as a low-cost retinal image analysis technique to automatically diagnose various retinal illnesses utilising body structure pictures. These are modern iterations of ANNs that take advantage of the abundance of available data. Larger neural networks employ them to deal with semi-regulated problems when a substantial amount of incoming input is untagged [20].

3.2.1 Convolution Neural Network

CNN is one of the layered perceptron variants. CNN can have more than one convolution layer and the network is very deep and has lower complexity. CNN is quite good at recognizing and recognizing distinct visual patterns. The CNN architecture for image classification [12,14].

CNN Classification

1. Convolution Layer
2. Pooling Layer
3. ReLU Layer(Rectified Linear Unit)
4. Dropout layer
5. Fully Connected Layer
6. Classification Layer

3.2.2 Efficient Net

EfficientNet is a convolutional neural organisation style and scaling approach that systematically scales all components of profundity/width/goal via a compound constant. Unlike standard practice, which arbitrarily scales these variables, the EfficientNet scaling approach consistently adjusts network dimension, profundity, and purpose using a set of fixed scaling factors.

3.2.3 VGG 16

A ConvNet is another name for a form of the artificial neural network is a convolutional neural network. A convolutional neural network is made up of an input layer, an output layer, and numerous hidden layers. One of the top computer vision models to date is the CNN (Convolutional Neural Network) variant known as VGG16. This model's developers analyzed the networks and enhanced the depth using an architecture with incredibly tiny (3 3) convolution filters, which demonstrated a notable advancement over the state-of-the-art setups. The depth was increased to 16–19 weight layers, yielding around 138 trainable parameters. The number 16 in VGG16 refers to 16 weighted layers. VGG16 has a total of 21 layers, including three dense layers, five Max Pooling layers, and thirteen convolutional layers. Although only sixteen of them are weight layers, also known as learnable parameters layers.

1000 photos from 1000 distinct categories may be classified with 92.7% accuracy using the object detection and classification algorithm VGG16. It is one of the most used image classification methods.

3.2.4 RESNET

A novel architecture called Residual Network was launched by Microsoft Research experts in 2015 with the proposal of ResNet. Residual Network: This design proposed the idea of Residual Blocks to address the disappearing gradient issue.

An artificial neural network (ANN) is called a residual neural network (ResNet)[32]. It is an extremely deep feedforward neural network with hundreds of layers that is the first functioning neural network to go so far. To skip some levels, utilize shortcuts or skip connections. Typical ResNet models are constructed using batch normalization in between two or three-layer skips that contain ReLU nonlinearities.

In tiny networks like ResNet 18, and 34 each ResNet block is either two layers deep or three layers deep (ResNet 50, 101, 152). This 3-layer bottleneck block is substituted for each 2-layer block in the 34-layer net to create a 50-layer ResNet. It is simple to train networks with several layers—even thousands—without raising the learning percent error. By applying identity mapping, ResNets assist in solving the vanishing gradient problem.

3.2.5 Mobile Net

A specific kind of convolutional neural network called MobileNet was created for use in both embedded and mobile application domains. They are built on an efficient design that makes use of depthwise separable convolutions to create compact deep neural networks that can operate with minimal latency on embedded and mobile devices.
There are 53 layers in MobileNet. The database contains a pre-trained version of the network that has been trained on more than a million photos. The pre-trained network can categorize photos into 1000 different item categories, including several Images.

A type of convolutional neural network model known as MobileNets are compact, low-latency, and low-power models that may be utilized for classification, detection, and other typical tasks. These are regarded as excellent deep-learning models for usage on mobile devices because of their moderate size.

3.3 Proposed Model for Image Classification

When the level of blood glucose in the blood exceeds the recommended level, polygenic illness develops. Polygenic disease gradually destroys the membrane veins, producing in diabetic retinopathy (DR), the major cause of helpless vision and visible deficiency. If the condition is found early on, treatment can be postponed or prevented. The pre-programmed location of diabetic retinopathy allows ophthalmologists to give better treatment to their patients. All of the techniques employing CNN have a restricted variety of photo possibilities due to their better accuracy.
Using the deep learning algorithms CNN,Efficient net, VGG 16, Mobile Net, and RESNET 50 classify all options into multiple categories to determine the severity of Diabetic Retinopathy via way of means of growing accuracy of each category as shown in figure 1.

By changing the parameters like stride, and padding and added some extra hidden layers in these models to achieve better accuracy. The proposed work focused on CNN, Efficient Net, VGG 16, Mobile Net, and RESNET 50 because Top1 and top 5 accuracies of these models are good as compared to other models as per the Keras application. The average Top1 accuracy is 77% and the average Top5 accuracy is 93%.

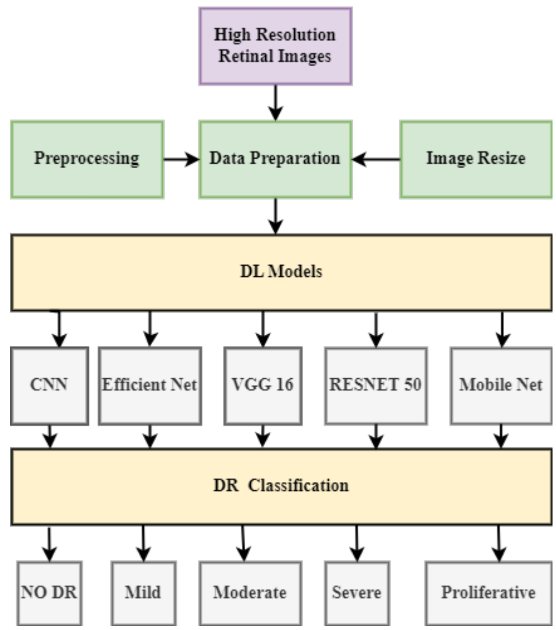


Figure 1 Proposed Deep Learning Model for Image classification.

3.3.1 Algorithm for Proposed Model

Step 1: Take High-Resolution Images as input.
Step 2: Pre-processing,Data Preparation,Image Resize apply on eye images.
Step 3: Deep Learning models are applied for classification is given below.
CNN-Convolution neural network
Efficient network
ResNet 50
MobileNet
VGG 16
Step 4: Performance analysis matrix
a). Training and testing
Step 6:Result and Analysis.

3.4 Implementation of the Deep Learning Models

The proposed model consists of CNN, Efficient Net, VGG 16, RESNET 50, and Mobile Net for DR classification shown in figure 1. In this model,high-resolution retinal images are provided, and after that preprocessing is done. Images are given to Various Deep Learning Models and then classify DR into 5 classes. 0 to 4 classes through CNN, give 0 for No DR, 1 for Mild,2 for Moderate,3 for Severe, and 4 for Proliferate shown in table1.

Table 2 Confusion Matrix

		ACTUAL	
PREDICTION		**Negative**	**Positive**
	Negative	True Negative	False Negative
	Positive	False Positive	True Positive

3.4.1 Performance Evaluation Metrics

1. Confusion Metrix
2. F1Score
3. Model accuracy
4. Model loss
5. precision
6. recall

Table 2 shows the Confusion Matrix size of the matrix is 2×2 for binary classification with actual values on one axis and foretold on another. Confusing terms square measure within the confusion matrix: True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP). Percentage of actually Positive from Out of all the positive foretold.

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

$$Error\ Rate = \frac{FP + FN}{TP + TN + FP + FN}$$

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

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

$$F1\ score = \frac{2 * (\text{Precision} + \text{Recall})}{\frac{(\text{Precision} + \text{Recall})}{\text{Recall}}}$$

Accuracy: It indicates the frequency at that the model accurately predicts the result.
Error Rate: It indicates the frequency at that the model accurately predicts the result.
Precision: The percentage of accurate positive predictions to total positive predictions is known as precision.
Recall: It is described as the positive categories predicted correctly by our model out of all positive categories.
F1 Score: It's tough to compare two models that have less precision and more recall. For this,compute the F1-score. The F1-score is maximal if the recall equals the precision.

4.0 RESULTS AND DISCUSSION

A CNN model was trained and evaluated on the pictures during epoch 20. When the photos were fed into CNN for training, an accuracy of 0.9834 and a testing accuracy of 0.7741 were obtained. Precision of 0.8478 for training and 0.8188 for testing. Similarly, accuracy of 0.8378 for training and 0.8098 for testing, F1-score of 0.7002 for training and 0.6573 for testing, Recall 0.5645 for training 0.5523 for testing, Loss 1.4521 for training 1.7010 for testing were achieved, as shown in table 3.

Table 3 CNN Model, For epoch=20

For Epoch 20	CNN Model	
	Train	**Test**
Accuracy	0.9834	0.7741
Precision	0.8478	0.8188
F1-Score	0.7002	0.6573
Recall	0.5645	0.5523
Loss	1.4521	1.7010

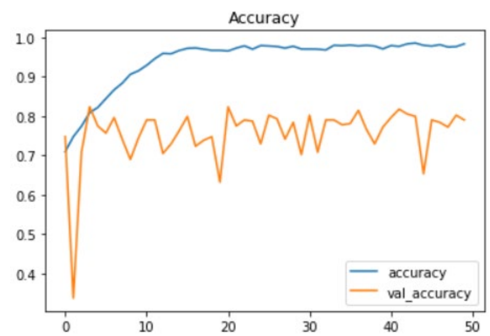


Figure 2. Accuracy for CNN Model

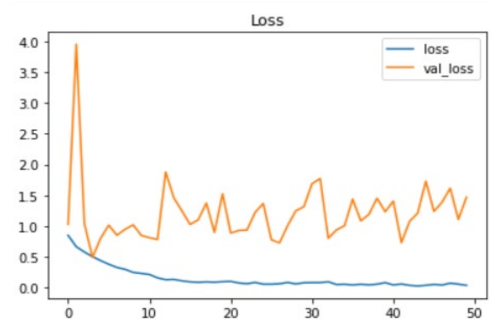


Figure 3. Loss for CNN Model

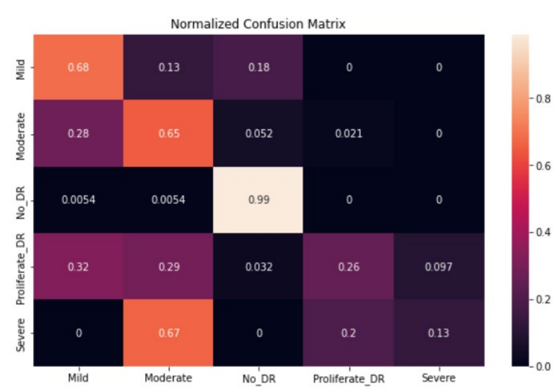


Figure 4. Confusion Matrix CNN

Figure 2, figure 3 and figure 4 shows Accuracy, Loss and Confusion matrix of CNN that classifies the images of DR. According to the confusion matrix it identifies the detection accuracy of No DR is 0.99, Mild is 0.68, Moderate is 0.65, Severe 0.13 and Proliferative 0.26.

Table 4. Efficient-Net Model

For Epoch 20	**Efficient Net Model**	
	Train	**Test**
Accuracy	0. 9825	0. 7520
Precision	0.9223	0.8200
F1-Score	0.9121	0.8404
Recall	0.8927	0.8101
Loss	1.5490	1.70742

Table 4 shows the graph of Accuracy, Precision, F1 score, recall, and loss of Efficient-Net for epoch 20. Blueline indicates training and orange indicate testing.

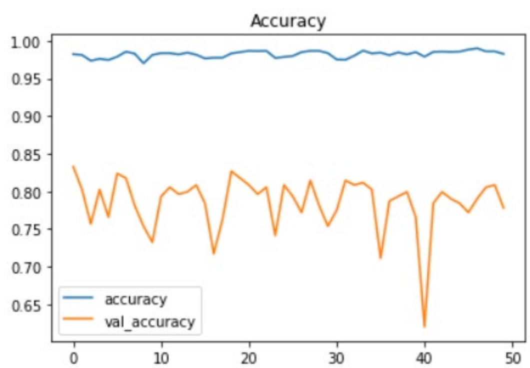


Figure 5. Accuracy of the Efficient Net Model

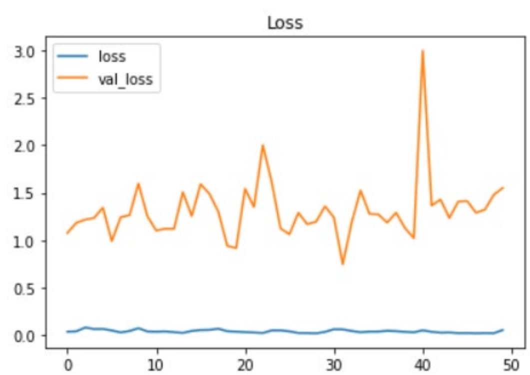


Figure 6. Loss of efficient net Model

Train and test the images by using the Efficient-Net model for epoch 20. The training accuracy of 0.9825 and a testing accuracy of 0.7520 is achieved by efficient net. Similarly, precision is 0.9223 for training and 0.8200 for testing, for F1-score is 0.9121 for training and 0.8404 for testing, for Recall 0.8927 for training 0.8101 for testing, for Loss 1.5490 for training 1.70742 for testing shown in table 4 and in figures 5 and 6.

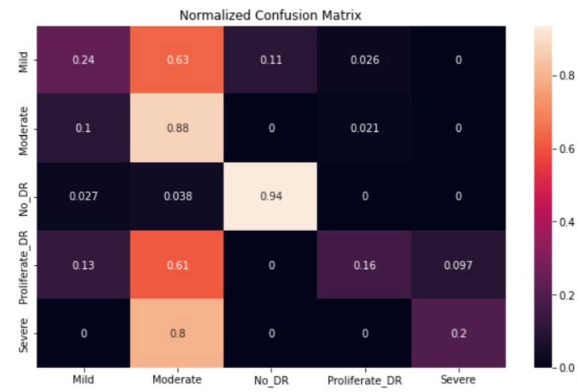


Figure 7. Confusion Matrix Efficient-Net

The figure 7 shows the confusion matrix of the Efficient-Net model, which classifies the images. The confusion matrix identifies the accuracy of No DR is 0.94, Mild is 0.24, Moderate is 0.88, Severe 0.2 and Proliferative 0.16.

Table 5.VGG 16 Model,For epoch=20

For Epoch 20	**VGG 16 Model**	
	Train	**Test**
Accuracy	0.7884	0.7712
Precision	0.7717	0.7611
F1-Score	0.7635	0.7696
Recall	0.7775	0.7710
Loss	0.2113	0.7111

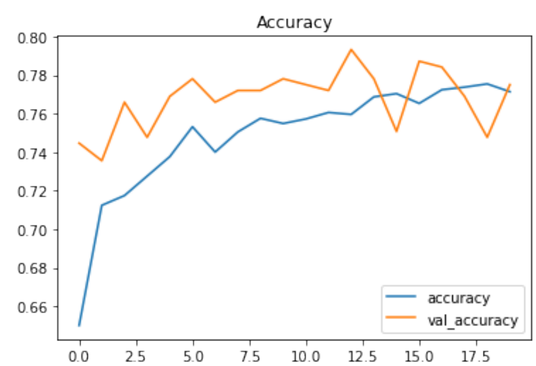


Figure 8. Model accuracy of the VGG 16 Model for Epoch 20

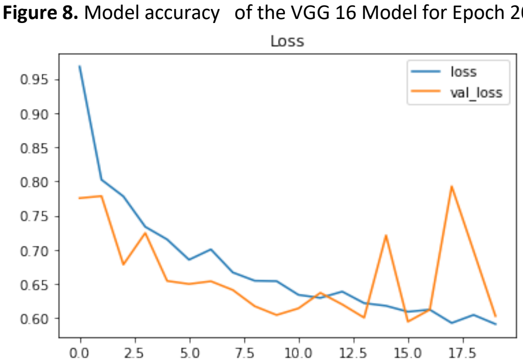


Figure 9. Model Loss of the VGG 16 Model for Epoch 20

Train and test the images by using the VGG 16 model for epoch 20. Training accuracy of 0.7884 and a testing accuracy of 0.7712 is achieved. Similarly, for precision of

0.7717 for training and 0.7611 for testing, for F1-score of 0.7635 for training and 0.7696 for testing, for Recall 0.7775 for training 0.7710 for testing, for Loss 0.2113 for training 0.7111 for testing shown in table 5 and in figures 8 and 9.

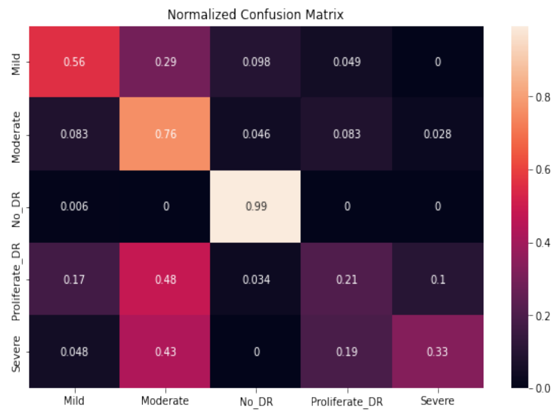


Figure 10. Confusion Matrix VGG16

The figure 10 shows the confusion matrix for VGG 16 model, which classifies the images of DR According to the confusion matrix it identifies the detection accuracy of No DR is 0.99, Mild is 0.56, Moderate is 0.76, Severe is 0.33, Proliferative is 0.21.

Table 6 RESNET 50 Model,For epoch=20

For Epoch 20	RESNET 50 Model	
	Train	**Test**
Accuracy	0.9329	0.8116
Precision	0.9029	0.7925
F1-Score	0.8965	0.7767
Recall	0.9063	0.7882
Loss	0.1733	0.8984

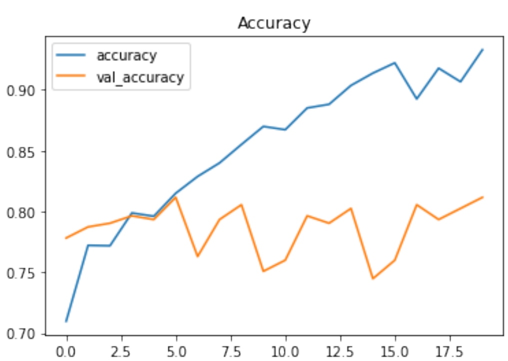


Figure 11. Model Accuracy the RESNET 50 Model for Epoch 20

Figure 12. Model Loss the RESNET 50 Model for Epoch 20

Train and test the images by using the ResNet 50 model for epoch 20. Training accuracy of 0.9329 and a testing accuracy of 0.8116 is achieved. Similarly, precision of 0.9029 for training and 0.7925 for testing, for F1-score of 0.8965 for training and 0.7767 for testing, for Recall 0.9063 for training 0.7882 for testing, for Loss 0.1733 for training 0.8984 for testing shown in table 6 and in figures 11 and 12.

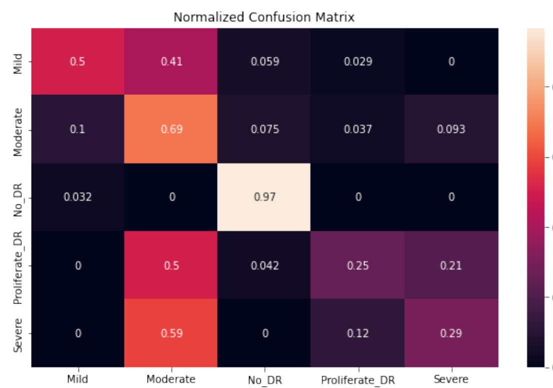


Figure 13 Confusion Matrix for RESNET 50 Model

The figure 13 shows the confusion matrix of the Res Net model, which classifies the images of DR. According to the confusion matrix it identifies the detection accuracy of No DR is 0.97, Mild is 0.5, Moderate is 0.69, Severe 0.29 and Proliferative 0.25.

Table 7 MobileNET 50 Model,For epoch=20

For Epoch 20	MOBILENET Model	
	Train	**Test**
Accuracy	0.9184	0.7752
Precision	0.8817	0.7623
F1-Score	0.8835	0.7632
Recall	0.8975	0.7771
Loss	0.2211	0.7217

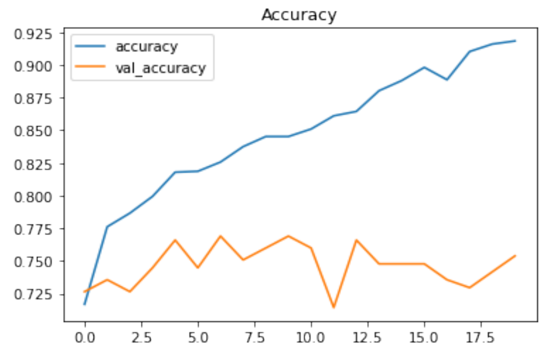


Figure 14 Model Accuracy for the MobileNet Model for Epoch 20

Figure 15 Model Loss for the MobileNet Model for Epoch 20

Train and test the images by using the MobileNET Model for epoch 20. Training accuracy of 0.9329 and a testing accuracy of 0.8116 is achieved. Similarly, precision of 0.9184 for training and 0.7752 for testing, for F1-score of 0.8835 for training and 0.7632 for testing, for Recall 0.8975 for training 0.7771 for testing, for Loss 0.2211 for training 0.7217 for testing shown in table 7 and in figures 14 and 15.

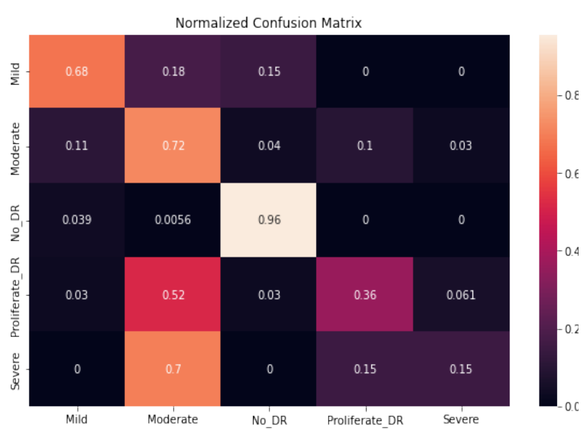


Figure 16 Confusion Matrix for MobileNET 50Model

The figure 16 shows the confusion matrix of the Mobile Net model, which classifies the images of DR. According to the confusion matrix it identifies the detection accuracy of No DR is 0.96, Mild is 0.68, Moderate is 0.72, Severe 0.15 and Proliferative 0.36.

Table 8: Comparison table of deep learning model

Models	Accuracy	
	Train	**Test**
CNN	0.9834	0.7741
Efficient Net	0.9825	0.7520
VGG 16	0.7884	0.7712
ResNet 50	0.9329	0.8116
Mobile Net	0.9184	0.7752

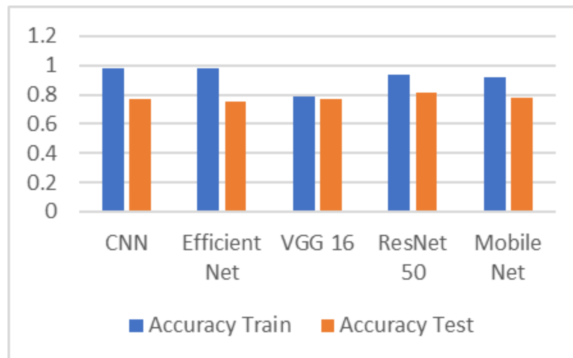


Figure 17 Bar graph for comparison of all deep learning model

Table 8 and figure 17 shows bar graph and comparison between 5 deep learning models. And hence these two models perform well as compared to the other 3 Models.

5.0 CONCLUSION AND FUTURE WORK

Diabetes leads to diabetic retinopathy, which affects the blood vessels in the retinal tissue of the eye. The previous approach for finding DR was laborious, costly, and time-consuming to manually diagnose with low accuracy. The proposed model implemented five deep learning Models based on CNN, Efficient Net, VGG 16, Res Net 50, and Mobile Net for image classification for detection of DR. For that, a total of 3662 retinal images are taken which split into 3296 train and 366 test images and worked on different epochs. This experiment was performed on 20 epochs, the model achieved classification accuracy for the CNN model is 77.41% for the test data set and the train data set 98.34%. In the Efficient Net model after 20 epochs the model achieved classification accuracy is 98.25% for the train data set and 75.20% for the test data set. In the VGG 16 model after 20 epochs the model achieved classification accuracy is 78.84% for the train data set and 77.12% for the test data set. In the Res Net 50 model after 20 epochs, the model achieved classification accuracy is 93.29% for the train data set and 81.16% for the test data set. In the Mobile Net model after 20 epochs the model achieved classification accuracy is 91.84% for the train data set and 77.52% for the test data set.

The proposed model achieved the highest accuracy which is 81% in Efficient Net as well as in ResNet. Hence, observed that these two models performed well as compared to the other 3 Models. In future work, if we focus on large data sets and the Quality of data, for better accuracy. Transfer learning models are data-hungry, requiring a large amount of data as well as high-quality data to develop the best model and produce good results. More data is required for multiclass classification to improve accuracy. Transfer learning models give high accuracy when trained on huge datasets.

Large datasets and high-quality data are prioritised for improved accuracy since they have a major bearing on how well machine learning algorithms work. Some reasons why are as follows:

(a) Large dataset: Machine learning algorithms learn and generalise patterns better with more data. Large datasets capture greater data complexity and variety and are more representative of the population. The system can better capture data subtleties and unpredictability with a bigger dataset, improving accuracy.

(b) Quality data minimises bias: A machine learning system is only as good as the data it learns from. Missing or faulty data might add bias and reduce algorithm accuracy. By assuring high-quality data, we can eliminate bias and increase algorithm accuracy.

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Conflicts of Interest

The authors declare no conflict of interest to any party.

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