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DEVELOPMENT AND ANALYSIS OF DEEP LEARNING MODEL BASED ON MULTICLASS CLASSIFICATION OF RETINAL IMAGE FOR EARLY DETECTION OF DIABETIC RETINOPATHY

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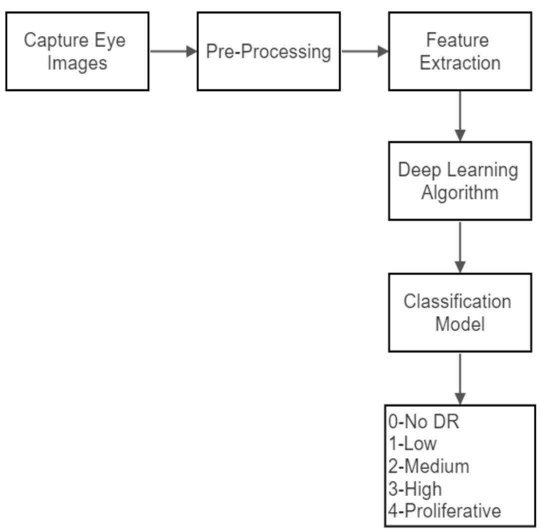
Graphical abstract



Abstract

Diabetic retinopathy (DR) is a leading cause of blindness, and early detection is crucial for effectively managing and preventing vision loss. This paper proposes a deep learning-based model for the early detection of diabetic retinopathy (DR) using retinal images. The proposed model uses a convolutional neural network (CNN) architecture and transfer learning-based EfficientNet architecture for multiclass classification (0- No DR, 1- Low, 2- Medium, 3- High, 4- Proliferative) of DR, on a large dataset of annotated retinal images. The performance of the model is evaluated on an independent test set and compared with CNN and EfficientNet methods. Results show that the efficient model achieves high accuracy and outperforms existing methods for DR detection. Moreover, the model can detect DR at an early stage, enabling timely interventions and preventing vision loss. The results show that we achieved a training accuracy of 94.42% after 20 epochs and a testing accuracy of 81.81%. The model's accuracy and early detection capability make it a promising tool for enhancing DR screening programs and enabling timely interventions to prevent vision loss.

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

1.0 INTRODUCTION

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 sends signals to the brain via a nerve at the bottom rear of your (optic nerve). Diabetes causes damage to blood arteries throughout the body. Sugar restricts the small blood arteries that attend your tissue layer, causing them to leak fluid or bleed, resulting in damage to your eyes. To compensate for the clogged blood vessels, the 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.[3] 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, as well as this research, can be quite useful. DR examination information for clinical ophthalmologists. T Chandrakumar et. al.[4] proved that during shading frame shape pics they experience and set up the DR`s completely surprising levels via CNN. They train and look at their version from the Kaggle dataset. Their result suggests that their version is applied for sleuthing all stages of DR and comparably as plays and contrasted with a change version via organized outfit version.
Kajaree Das et.al [5] analyzed ML giving the software the flexibility and agility it needs. ML will thrive shortly, despite

some applications (e.g., writing matrix multiplication programs) where it may not be advantageous. With greater information resources and a greater desire for customized configurable software, ML will succeed.

The structure of this research paper is as follows: **Section 2** is about the background and related work then **Section 3** introduces the methodology in which we briefly discuss the deep learning model for image classification, confusion matrix, CNN and Efficient Net, and Basic steps. **Section 4** describes the model performance in the Experimental results of various samples and briefly discussed the results, **Section 5** includes briefly discuss the result.**Section 6** summarizes and concludes the paper.

2.0 RELATED WORK

Authors S.Kajan et.al [1] programmed detection of diabetic retinopathy using a pre-trained convolutional neural system is suggested (CNN). The retinal pictures were preprocessed and used as training and testing material from the Diabetic Retinopathy Database, which was divided into five groups based on the appraisal of retinal injury. They compared and chose the best of three unique pre-trained neural networks based on order precision.

Authors C.Lam et al. [2] shown how to use convolutional neural networks (CNNs) on colored fundus pictures for the task of recognizing diabetic retinopathy. They also looked into multinomial characterization models, and their findings demonstrate that mistakes primarily occur when mellow illness is misclassified as common because CNN fails to recognize subtle infection highlights. They discovered that improving recognition of unaffected highlights requires preprocessing with distinguish restricted flexible histogram modification and ensuring dataset loyalty by master confirmation of class names. Mike Voets et.al[6] Using publicly accessible data, but after re-implementing the primary strategy from JAMA 2016; 316(22), they were unable to get the same outcomes as those described in that paper. It is possible that some of the differences in results can be attributed to the original study's access to higher-quality data than what is now made accessible to the general public.

Jen HongTan et al.[7] Exudates, hemorrhages, and micro-aneurysm segmentation is a difficult task. The majority of the methods presented simply addressed having problematic characteristics. They created an algorithm that used a 10-layer convolutional neural network to separate and classify exudates, hemorrhages, and micro-aneurysms automatically and simultaneously. Before being fed into the net, the input image was normalized. The CLEOPATRA database was used to train and test their technique.

Nitigya Sambyal et al [8] In this study, a method for pixel-smart segmentation of retinal lesions—including microaneurysms and exudates—has developed. IDRiD and e-ophtha data sets. The community uses a modified UNet structure with a pre-trained ResNet34 encoder. Semantically, exudates and microaneurysms are divided. a database created using the fundus.

Andrzej Grzybowski1et al.[9] Artificial intelligence is being used increasingly in ophthalmology. In recent years, a number of innovative screening methods have been presented with significant detection claims. But just a few of these are really in use right now. It is a purchaseable item. AI-assisted DR detection may be useful. Nevertheless, they are crucial in the management of blindness.

Badar et al.[10] focussed on Deep neural network variations such as AlexNet, LSTM, VggNet, and GoogleNet which can be used to extract retinal structural components. Although Lee et al. [11] used VGG-16 for 3-D OCT retinal image analysis, there is no model for its usage with retinal fundus images. All of these networks are extremely deep, having the capacity to extract far more complicated characteristics than older approaches, as well as improved key metrics.

Authors Y. Luo et al. [12] explained that the SFCN is broken down into three fundamental parts. A few unshapely convolutional layers were utilized in the initial phase to eliminate CNN representations from the retinal picture and reconstruct the given retinal picture using various deconvolutional layers to finish the longer-term learning module. This procedure makes sure that the learned component depiction has enough information to develop. The preparation in the second part is governed by the fuzzy bunching computation's projected result. Finally, they succeeded in performing retinal image grouping using the completely automated method.

$z = f(x)$, The feature vector f victimization Li,e Encoder by stacking via constraints of convolution layers in the feature learning module from retinal image displays.

$$z = [h(L)1, \ldots\ldots, h(L)mL] \quad (1)$$

ml options map calculated.

$$Lre = 1/N \sum_{E x \varepsilon X} \| x\text{-}x \| 2 \quad (2)$$

Lre is reconstruction Loss.In the fuzzy self-supervision module,

$$Lss = 1/N \sum_{E x \varepsilon X} \| fss(Z)\text{-}\mu \|^2 \quad (3)$$

They reached Lss self-supervision loss,

$$NC \sum_{i=1} \mu i=1, \forall i=1, \ldots\ldots Nc \quad (4)$$

Retinal images are divided into two types for a single feature vector, comparable to Tar Heel State collections c. D [c1; : : : ; ci; : : : ; cNc], and also the possibilities be applicable to per cluster u D [u1; : : : ; ui; : : : ; uNc].

$$Lfs = 1/N \sum_{E x \varepsilon X} \sum_{i=1} \mu mi \| z - Ci \| 2, \text{ one one } m < \infty \quad (5)$$

Lfs is Fuzzy supervising Loss.

$$L = Lss + \alpha\ Lss + \beta Lfs \quad (6)$$

In total loss alfa, beta square measure balance parameter, L is the loss operate (final) of SFCN.

Yaxin Shenaet.al [13]suggested a method that assesses the fundus picture quality by using quality factor analysis to forecast the overall quality task in terms of artifact, clarity, and 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 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[14] 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 valuable tool for a retinal red lesion specialist and perhaps leading to more DR identification. The main goal was to simplify the model while improving 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 [15] In this research, a qualitative technique was employed to evaluate the unique influence of DR lesions throughout the fundus on the likelihood of PDR advancement. They discovered that haemorrhages farther from the foveal or ONH core, as well as their frequency and surface area, appeared to be associated with a greater risk of advancement. Surprisingly, more peripheral CWS were identified as a potential side effect for the progression of PDR when this quantitative grading method was applied, but not IRMA. Machine learning is likely to alter people's perceptions about computer science in general, in addition to software design.

Authors Amita Mesram , Dr. Deepak Dembla , Dr. Reema Ajmera [16] are analyzed different DL Algorithms for early detection of DR. Diabetic retinopathy is critical.

Balazs Harangi et al.[17] In this research, they propose an ensemble-based neural network architecture for recognizing MAs in fundus images. Their model connects various DCNNs to one another. permits their concurrent training 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. [18] In a broad variety of medical imaging applications, current CNN designs have installed contemporary outcomes. They advocate a multi-challenge learning addition to the U-Net architecture: rather than a single encoding module, more than one deciphering module is used for green classification. They recommend encoding module improvements primarily based totally on current CNN breakthroughs, along with residual connections in any respect scales, blended pooling for spatial compression, and massive kernels for convolutions at the bottom scale.

Avula Benjamin et al. [19] 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 impacted fundus picture. The presented model has more than 90% accuracy in detecting hard exudates.

Gazala Mushtaqet.al [20] they attempted to deliver their deep learning methodology for retinal clinical prediction using a DenseNet169 and offered a thorough analysis of different methods for autonomously detecting diabetic retinopathy. (which is a new CNN architecture, having many deep layers). To compare the outcomes, they used a regression model in addition to the DenseNet-169 classifier.

Li, Fangjun, et al.[21] On the EyePACS dataset, their model obtains new state-of-the-art outcomes in the job of diabetic retinopathy evaluation. Additionally behavior systematic exams of have an impact on picture resolution, demonstrating that because the device develops with improved enter picture resolutions, overall performance grows logarithmically, while each time and computation value grows tremendously.

Authors Dolly Das et.al [22] cover DR, including its symptoms, features, shape, size, and location, as well as how DR leads to blindness. It also covers several ML and DL strategies for detecting abnormal RBV behavior and OD for detecting DR lesions, such as in chronological order, MAs, HEs, EXs, CWS, FAZ, IRMA, and Neovascularization.

Authors G. U. Nneji et.al [23] A graded fusion-based DR identification method that can simultaneously analyze CLAHE and CECED fundus images was developed in their study. As previously stated, these channels are combined to acquire significant features from fundus images and improve identification accuracy. To get the most out of the visual characteristics gathered from the various channels, the weighted fusion method was used. The proposed WFDLN model addresses the issue of low-quality fundus images by combining the weighted features provided by the CLAHE and CECED pre-processing phases.

Authors T.Hui et.al. [24] proposed TLBO (Teaching-learning-based optimization) enhanced SVM on arrangement stage after system training. It is a PC-supported output for programmed diabetic retinopathy analysis that applies fragmented max-pooling approach in both (Deep convolutional neural network) DCNN organise and. For this problem, they were using an unique characterisation method based on the most current developments in deep learning and computer vision.

3.0 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 below in Table 1.

Table 1 Images are divided into a Category

Image Category	Count
Mild	370
Moderate	999
No_DR	1805
Proliferate	193
Severe	295
Total Images	3662

That retinal pictures are taken from various places as well as various devices due to that a lot of noises are included with that picture, which isn't good.It appears that something needs to be eliminated, necessitating many preprocessing procedures. For diabetic patients on a scale of 0 to 4, the retinopathy associated with each image was scored as follows:

- 0- No DR
- 1- Low
- 2- Medium
- 3- High
- 4- Proliferative

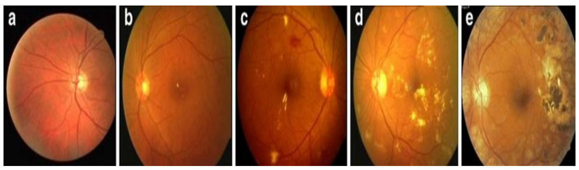


Figure 1 Retinal Image shows (a) No DR (b) Low DR (c) medium DR (d) High DR (e) proliferative DR[20]

In Figure 1a. 0-No DR- signifies that no symptoms are present in the retinal image related to DR.In figure b.1-Low DR represents that various features are available in the retinal image such as Haemorrhages, hard exudates, and Macular Edema, In figure c. 2-Medium DR signifies the presence of widespread Haemorrhages, figure d. 3-High DR indicates the presence of Haemorrhages in four quadrants, Venous Beading in two quadrants, fig. e.4-proliferative DR indicates Pre Retinal Hemorrhages [15].

4.0 METHODOLOGY

4.1 Proposed Deep Learning Model for Image Classification

In the previous section, we discussed the current approaches for detecting diabetic retinopathy. When the level of blood glucose in the blood exceeds the recommended level, polygenic illness develops. Polygenic illness damages the membrane veins over time, resulting in diabetic retinopathy (DR), which is the leading cause of helpless vision and apparent deficit. If the illness is discovered early, the therapy will prevent the occurrence and can be postponed. Diabetic retinopathy's pre-programmed location permits ophthalmologists to provide better care to their patients. Because of its high accuracy, all of the approaches involving CNN have a limited selection of photo options.

In our proposed algorithmic rule, we tend to extract all special features, and optic disc taken from retinal images via way of means of preprocessing. Then, using the deep learning algorithms CNN and Efficient net, 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 2.

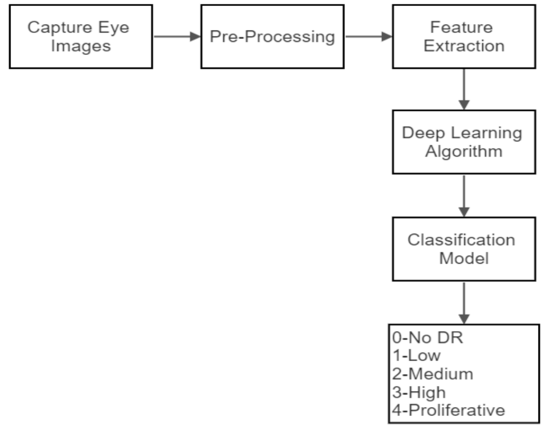


Figure 2 Proposed Deep Learning Model for Image classification

Basic Steps for Implementation of the Proposed Deep Learning Model

Step 1: Take varied Retinal pictures as input.
Step 2: Pre-processing from eye picture information.
Step 3: Feature Extraction
Step 4: Deep Learning model applied for classification is given below.
CNN-Convolution neural network
Efficient network
Step 5: Performance analysis matrix
a). Training and testing
Step 6:Result and Analysis.

There 2 major approaches that we will bear in the current situation, which are

Image classification victimizationCNN
Image classification victimization-Google's EfficientNet.

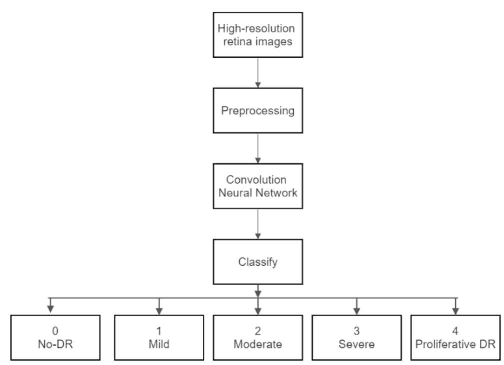


Figure 3 CNN for DR classification

Table 2 Confusion Matrix

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

In the above figure 3, we use CNN for DR classification.In this model, we provide High-resolution retinal images, and after that preprocessing is done and classify DR into 5 classes. 0 to 4 classes throughCNN,give 0 for No DR, 1 for Mild,2 for Moderate,3 for Severe,4 for Proliferate shown in table1.

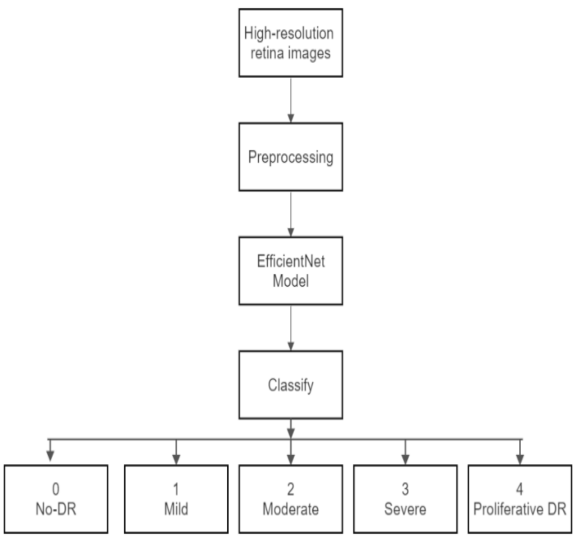


Figure 4 EfficientNet for DR classification

Figure 4 shows the Efficient Net Model for DR classification. In this model, we provide High-resolution retinal images, and after that preprocessing is done and classify DR into 5 classes. 0 to 4 classes thru CNN give 0 for No DR, 1 for Mild,2 for Moderate,3 for Severe,4 for Proliferate shown in table 1.

4.2 Performance Evaluation Metrics

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

In 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.

$$\text{Precision} = \frac{TP}{TP+FP} \qquad [7]$$

The value of Precision lies between 0 and 1.

$$\text{Recall} = \frac{TP}{TP+FN} \qquad [8]$$

F1Score takes both False Positive and False Negative.

$$\text{F1 score} = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = \frac{2*(\text{Precision} + \text{Recall})}{(\text{Precision} + \text{Recall})}$$

4.3 Deep Learning Model for Image Classification

This step is critical for making the procedure less difficult. The images are then metameric, separating them into many categories. Following pre-processing, Feature Extraction is performed, during which several choices are extracted from the image understanding, such as Optic Distance, vessel, carried out scientific Entropy Exudates space, and chemical evaluation of these options is accomplished. Through the use of the Deep Learning algorithmic program, the extracted alternatives from the picture are chosen and categorized. There are a few different types of alternative region devices. The accuracy of each class, as well as the overall accuracy of the class, is improved as a result. We have used Python 3.5 and libraries such as NumPy, Panda, Matplotlib, Scikitlearn, Seaborn, tools in this procedure to improve and extend the visual impairment detection method, depending on the needs of the analysis.

4.3.1 Deep Learning Algorithm

Deep learning is gaining popularity as a low-cost retinal image analysis method. Using a Convolution Neural Network (CNN) and a low-cost Internet to automatically identify different retinal illnesses using body structure images. These are contemporary versions of ANNs that take advantage of today's abundant data supply. They're employed in larger neural networks to solve semi-regulated problems in which a significant amount of incoming data is untagged or unclassified [25].

4.3.2 Convolution Neural Network

CNN is one of the layered perceptron's 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] is shown in figure 5.

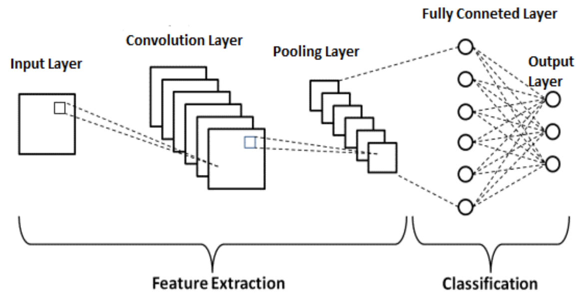


Figure 5 A CNN Architecture to classify Image

CNN Classification

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

1. Convolutional Layer
   This is the most significant layer that appears when a statistical image needs to be classed. Local receptive fields and Shared hundreds form the foundation of the convolutional neural organization region unit. For image recognition, these region devices construct a deep convolutional neural network.
2. Pooling Layer
   This is one of the most important layers that help the community avoid over minimizing the amount of factor computation required by the majority of the community. It's a type of non-linear downsampling that works. Pooling divides the activation maps into hard and fast rectangles, allowing the most charge to be obtained for the majority of the sub-region. ReLU.
3. Layer(Rectified Linear Unit(ReLU))
   Rectified Linear Unit(ReLU) layer is an activation function. This activation operation induces a lack of many of the hidden units. Also, it's been proven that the deep neural networks location unit is normally skilled expeditiously.
4. Dropout layer
   The widespread piece of the deep convolutional neural organization is dealing with the limits produced from each stacked layer plenteously. It`d motive over-fitting. For retaining in different from such things, losing out positive neurons most of the layer that fell to the following layer. The use of dropout is basically on the point of the entire related layer.
5. Connected Layer
   The layer that comes as soon as the flowed convolutional conjointly, max/ordinary pooling layer is known as a related layer. The popular thinking is finished thru this residue all through the arrangement. A related layer takes all nerve cells from the various beyond layers from the max-pooling layer and associates them to every neuron.
6. Classification Layer
   After the stacked or deep exclusive layers, the ultimate layer may also be a softmax layer. which stacked closer to the best for characterizing the shape picture accompanied through the related layer yield. Here, the choice is a single class or multiclass class.

4.3.3 Efficient Net

EfficientNet may be a convolutional neural organization style and scaling strategy that systematically scales all parts of profundity/width/goal utilizing a compound constant. Not in the slightest degree like regular follow that discretionary scales these variables, the EfficientNet scaling technique systematically scales network dimension, profundity, and goal with a bunch of fastened scaling coefficients.

5.0 RESULTS

We compare a method with a CNN and Efficient Net Model for image classification that was trained and Tested the images for epoch 20. When we apply images to CNN model for training we got an accuracy of 0.7134 and a Testing accuracy of 0.7141. Similarly, we got for a precision of 0.8378 for training and 0.8098 for testing, for F1-score of 0.6902 for training and 0.6673 for testing, for Recall 0.5943 for training 0.5723 for testing, for Loss 0.7802 for training 0.8612 for testing shown in Table 3.

Table 3 CNN Model, For epoch=20

For Epoch 20	CNN Model	
	Train	**Test**
Accuracy	0.7134	0.7141
Precision	0.8378	0.8098
F1-Score	0.6902	0.6673
Recall	0.5943	0.5723
Loss	0.7802	0.8612

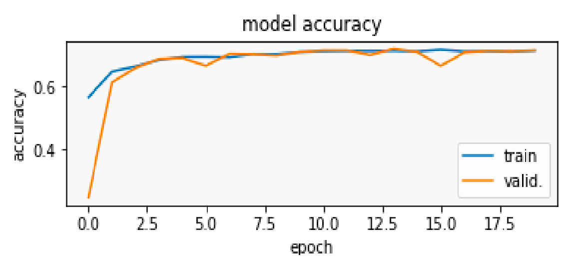


Figure 6. Model Accuracy of CNN for epoch 20

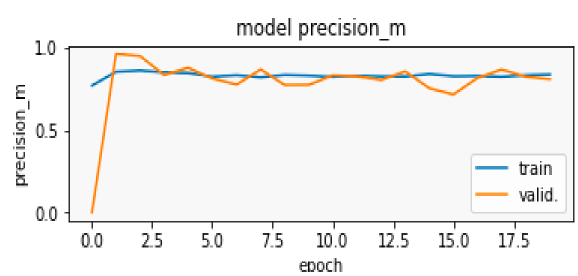


Figure 7. Model precision for epoch20

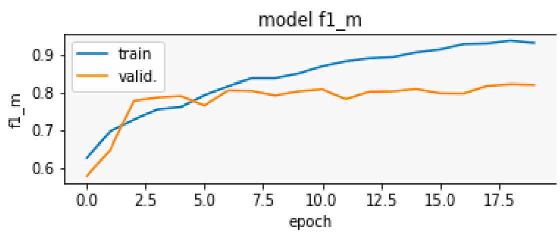


Figure 8 Model F1-Score of CNN for Epoch 20

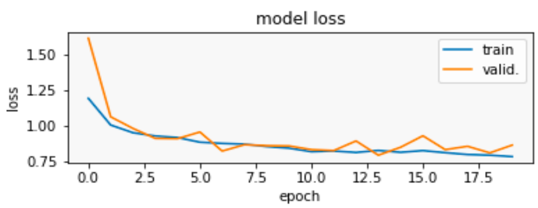


Figure 9 Model Loss of CNN for Epoch 20

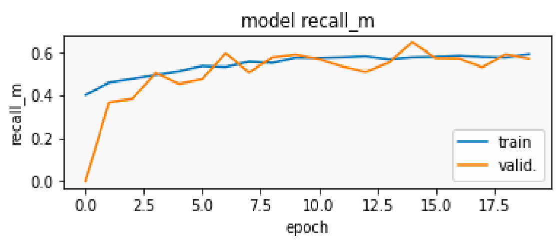


Figure 10 Model Recall of CNN for Epoch 20

Figure 6 shows the graph of model accuracy, Figure 7 shows precision, Figure 8 shows F1 score, Figure 9 shows the model Loss of CNN, and Figure 10 shows model Recall of CNN model for epoch 20. Blueline indicates training and orange indicate testing. Again images are applied to the Efficient-Net model achieving both higher accuracy and better performance over the present CNNs model. We train and Test the images by using the Efficient-Net model for epoch 20. When we apply images for training we got an accuracy of 0.9342 and a testing accuracy of 0.8181. Similarly, we got for a precision of 0.9456 for training and 0.8341for testing, for F1-score of 0.9317for training and 0.8205for testing, for Recall 0.919for training 0.8078for testing, for Loss 0.1795 for training 0.7218for testing shown in Table 4.

Table 4. Efficient-Net Model,For epoch=20

For Epoch 20	EfficientNet Model	
	Train	**Test**
Accuracy	0.9342	0.8181
Precision	0.9456	0.8341
F1-Score	0.9317	0.8205
Recall	0.919	0.8078
Loss	0.1795	0.7218

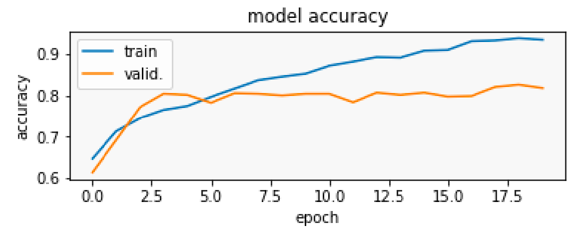


Figure 11 Model accuracy of the Efficient Net Model for Epoch 20

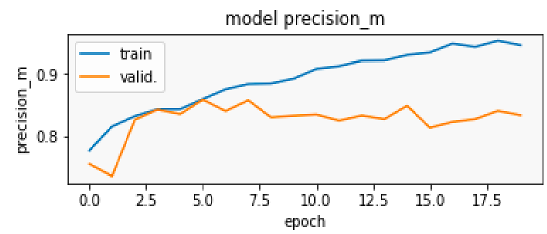


Figure 12 Model precision of Efficient Net Model for Epoch 20

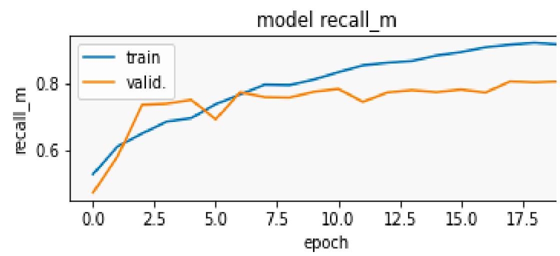


Figure 13 Model Recall of efficient net Model for Epoch 20

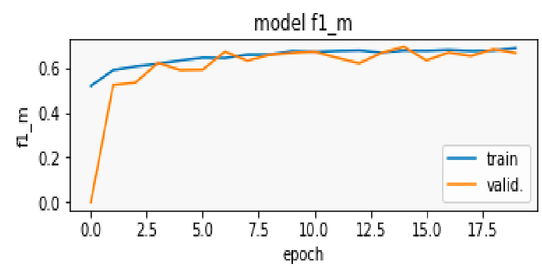


Figure 14 Model F1-Score of EfficientNet Model for Epoch 20

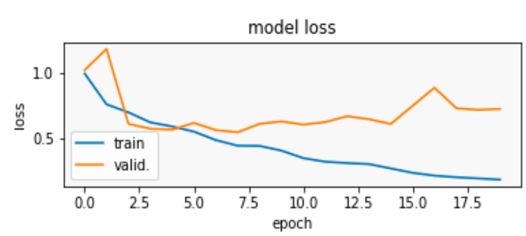


Figure 15 Model Loss of efficient net Model for Epoch 20

The Figure11 shows the graph of accuracy, Figure 12 shows precision, Figure 13 shows recall, Figure 14 shows F1 score, and Figure 15 shows loss for Efficient-Net on epoch 20. Blueline indicates training and orange indicate testing.

6.0 DISCUSSION

Diabetic retinopathy (DR) is a primary cause of blindness, and early identification is critical for controlling and avoiding visual loss. Manually it is very difficult to diagnose DR. So to diagnose automatically and accurately the results got by automation.

Hence from the results,that compared and analyzed the accuracy,precision,F1 score and model loss of two transfer learning models CNN and EFFICIENTNET that we have implemented. EFFICIENTNET model achieved better and more accurate accuracy. Accurate accuracy is very important for detecting Diabetic Retinopathy in its early stages.

The early identification of diabetic retinopathy (DR) utilising retinal pictures is addressed in this article using a deep learning-based approach. For multiclass classification (0- No DR, 1- Low, 2- Medium, 3- High, 4- Proliferative) of DR, the proposed model combines a convolutional neural network (CNN) architecture with a transfer learning-based EfficientNet architecture.

In image classification tasks, imbalance datasets are common, and addressing them is crucial to achieve accurate and reliable results. Here are some techniques that can be used to handle imbalance datasets in image classification tasks with deep learning models:

Data Augmentation: This technique involves generating additional training data by applying image transformations such as rotation, flipping, scaling, and adding noise to the existing images. Data augmentation can help balance the dataset by creating new instances of the minority class.

Transfer Learning: Pretrained models can be fine-tuned on the imbalanced dataset to leverage the knowledge learned from a larger dataset. The fine-tuned model can then be used to predict the class labels of the imbalanced dataset.

Ensemble learning: Ensemble learning involves training multiple models on different subsets of the dataset and combining their predictions to obtain the final result. This can help improve the accuracy and reliability of the predictions.

By using one or more of these techniques, we can handle the imbalance dataset in image classification tasks before implementing the deep learning model and improve the accuracy and reliability of the predictions.

7.0 CONCLUSION AND FUTURE WORK

Damage to the blood vessels in the tissue on the retina of the eye due to high blood sugar levels causes diabetic retinopathy. The old method for detecting DR is time-consuming, difficult, expensive, and required more time to diagnose manually. It also gave low accuracy. We have proposed a method with two Deep Learning models based on CNN and Efficient Net for image classification for detection of DR. For that, we have taken a total of 3662 retinal images and worked with different epochs. We conducted an experiment in which we observed that with 20 epochs we achieved classification accuracy in the CNN model is 71.34% for the training data set and for the testing data set we achieved 71.41%. In the Efficient Net model after 20 epochs,we have achieved 93.42% accuracy for the training data set and 81.81% for the testing data set. The accuracy of the efficient net is better than CNN.Even though it is not good accuracy due to lack of data set. In future work, if we focus on large data sets and Quality of Data then we will achieve better accuracy.

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