Deep Learning Based Identification and Categorization of Various Phases of Diabetic Retinopathy

Reem Jawed[1], Muhammad Ahsan Ansari[2], Syed Muhammad Shehram Shah[3], Jawed Ahmad Unar[4], Khair Muhammad Unar[5], Sammer Zai[6]

[1]Institute of Information and Communication Technology (Mehran University of Engineering and Technology, Jamshoro).

[2]Department of Computer Systems Engineering (Mehran University of Engineering and Technology, Jamshoro)

[3]Department of Software Engineering (Mehran University of Engineering and Technology, Jamshoro)

[4]Department of Data Science (Quaid-e-Awam University of Engineering, Science & Technology, Nawabshah)

[5]Postgraduate Student at Institute of Information and Communication Technology (Mehran University of Engineering and Technology, Jamshoro)

[6]Department of Computer Systems Engineering (Mehran University of Engineering and Technology, Jamshoro)

***Correspondence:** Sammer Zai, sammer.zai@faculty.muet.edu.pk

Citation | Jawed. Reem, Ansari. M. A, Shah. S. M. S, Unar. J. A, Unar. M. K, Zai. S, "Deep Learning Based Identification and Categorization of Various Phases of Diabetic Retinopathy", IJIST, Vol. 6 Issue. 2 pp 772-784, June 2024

Received | May 26, 2024 **Revised |** June 18, 2024 **Accepted |** June 23, 2024 **Published |** June 26, 2024.

Diabetic Retinopathy is a growing disease that affects the human retina of diabetic patients, leading to loss of vision if left untreated. Early diagnosis and accurate classification of various stages of DR are crucial for immediate intervention and efficient control. Therefore, this study utilizes a Deep Learning (DL) model named Densenet121 to classify different stages of DR. The dataset used in this research contains collections of color fundus images obtained from diabetic patients, labelled with corresponding disease stages. The dataset used was taken from Kaggle; APTOS 2019. Standard metrics such as accuracy, recall, F1-score, and precision are used to measure the effectiveness of the proposed model. The proposed DL based classification model shows encouraging results and has achieved a high level of accuracy across various severity levels. This model offers an automated method for detection and classification of the disease facilitating early diagnosis. Overall, this study advances automated diagnosis to lessen the burden of diabetic retinopathy.

Keywords: DenseNet121 Model; Diabetes; Diabetic Retinopathy; Kaggle Dataset; Retina.

Introduction:

Diabetic Retinopathy (DR) is a widespread retinal complication which arises from long time diabetes, a chronic disorder due to which millions of people are affected. It is a major reason for loss of vision or blindness in young-age adults due to which it is a critical challenge for public health. In 2014, reports indicate that around 422 million people were affected by diabetes mellitus [1]. By the year 2020, it was estimated that there were around 103.12 million adults who were affected by DR. Looking ahead to 2045, projections indicate a surge in these figures to reach approximately 160.50 million individuals [2].

DR manifests as a complexity in both types of diabetes, arising from the detrimental impact of diabetes on the retinal blood vessels. The DR classification is divided into three distinct categories: NPDR (non-proliferative diabetic retinopathy), PDR (proliferative diabetic retinopathy) and DME (diabetic macular edema). NPDR is characterized by observable manifestations like microaneurysms, hemorrhages, and intraretinal microvascular abnormalities. PDR represents the more advanced phase of NPDR, marked by the emergence of new retinal blood vessels, which may result in retinal detachment. Macular edema materializes when the integrity of the blood-retina barrier (BRB) is compromised [3].

Timely identification of these changes through clinical assessment, such as fundus photography, remains a primary pillar for disease management. However, the subjectivity inherent in human interpretation, coupled with the increasing caseload, accentuates the demand for automated and objective solutions [4]. In the context of diabetic retinopathy, the utilization of deep learning techniques holds the promise of significantly improving diagnostic accuracy, enabling early intervention, and ultimately mitigating vision loss [5].

In the initial phases of DR, it is commonly known as NPDR, a categorization which is subdivided into Mild, Moderate, and Severe phases. In the mild stage, a solitary microaneurysm (MA), signified by a tiny circular red dot located at the terminus of blood vessels, is observed. Progressing to the Moderate stage, these microaneurysms rupture into deeper layers, giving rise to flame-shaped hemorrhages within the retina. The severe stage of NPDR exhibits a notable presence of over 20 intraretinal hemorrhages within each of four quadrants. This is coupled with distinct venous bleeding and pronounced intraretinal microvascular abnormalities. The PDR signifies the late or advanced stage of diabetic retinopathy, characterized by neovascularization—a natural process involving the creation of novel blood vessels within the shape of functional microvascular networks that form on the surface of inner retina [4].

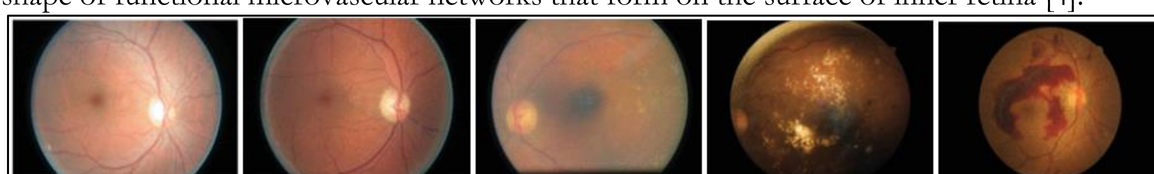

Figure 1: Various phases of Diabetic Retinopathy

Figure 1 illustrates various phases of Diabetic Retinopathy (DR) including Normal, Mild, Moderate, Severe, and PDR, and are shown accordingly in Figure. 1(a), Figure. (b), Figure. (c), Figure. (d), and Figure. (e), respectively. The ophthalmologist requires a lot of manual effort and time for the detection and classification of these phases of retinopathy in the middle stages which may lead to inaccurate detection due to manual process and eventually leads to vision loss. Additionally, it is challenging to identify and classify DR related disease through physical tests and examination. Therefore, computer aided techniques play a vital role to assist the ophthalmologist in accurately and timely identifying distinct phases of DR. AI-driven techniques including machine learning and deep learning has got various applications in healthcare for the automation of disease detection. In this paper, a deep learning-based approach has been used for the detection and classification of DR diseases.

The main aim of this study is to analyze the fundus images and classify different phases of diabetic retinopathy. The objectives to accomplish this aim are listed below:

- To detect DR in color fundus images
- To classify various phases of diabetic retinopathy
- To perform comparative analysis with existing models developed for detection and categorization of diabetic retinopathy.

The subsequent sections are structured as follows: Section II conducts a review of contemporary literature concerning the detection and categorization of various phases of diabetic retinopathy. The outlined methodology is expounded upon in Section III, with the subsequent Section IV housing the outcomes and subsequent discourse. The paper concludes in Section V.

Literature Review:

A lot of methods have been presented in the literature that focused on the task of automatic detection and classification of diabetic retinopathy. For example, Jabbar, et al. [6] proposed a framework to classify distinct phases of diabetic retinopathy by severity levels thus utilizing Google Net and Res Net models. Their model was trained to detect severity lesions such as cotton wool spots, venous beading etc. Their experimental results showed an accuracy of 94%. The publicly available datasets are imbalanced so to overcome these issues Atcı et al. [7] examine various cutting-edge techniques and thus obtained precision scores ranging from 76% to 96% throughout various phases of DR. Their results are noteworthy but still there is a need for more studies due to problems with the dataset, and generalizability to a group of patients. Lalithadevi, et al. [8] proposed an inventive Opti Dex model using deep learning and explainable AI for detection and classification of DR. The model achieved an accuracy of 97.65% but implementing such type of model in an environment with limited resources or clinics with no access to high performance computing is difficult. Mohanty, et al. [9] created a hybrid model, which is combination of two models VGG16 and Densenet121. They used the publicly available dataset from Kaggle named APTOS2019. Initially the dataset was not balanced so they balanced the dataset and underwent some preprocessing steps. Their hybrid model gave accuracy of 79.50%. Wong, et al. [10] proposed a method using transfer learning which utilizes the features of Resnet-18 and Shuffle Net for identification and classification of diabetic retinopathy. Their model gave an accuracy of 82% on APTOS dataset which is publicly available on Kaggle. Carrera, et al. [11] created a computer-assisted diagnostic that is based on the digital analysis of retinal pictures. In order to extract features that have been employed by SVM to determine the grade of each retinal image, blood vessels, micro aneurysms, and hard exudates are first isolated during the image processing process. On a database of 400 retinal pictures that were graded using NPDR's 4-grade system, the model was put to the test. They were able to achieve accuracy of 92.4% as a result. Similarly, Nguyen, et al. [12] developed an automated method for DR screening which has hastened the detection and decision-making processes currently carried out manually by ophthalmologists or other qualified clinicians by examining digital-colored images of the retina. They grade the severity of DR using their automated approach, which examines fundus snapshots with exceptional illumination and fields of view. The Eye PACS dataset from the Kaggle 2015 competition was used, and for this DR detection, CNN was integrated with VGG-16 and VGG-19, giving the system an accuracy of 82%. In another study, Qummar, et al. [4] proposed a model in which they trained an ensemble of five deep CNN models, Inceptionv3, Xception, Resnet50, DenseNet-169, and Dense121, using publicly available Kaggle datasets. This improved the classification of DR stages compared to the traditional models, and the ensemble's accuracy was 80.8%. Albahli & Yar [13] developed three deep learning models, ResNet50, VGG-19, VGG-16 to detect the extremity of DR from retinal images and determine whether it leads to macular edema. They used a small dataset and, thus, used three techniques to enhance the features of the images. Brightness, Color, and

Contrast enhancement (BCC), Color Jitter (CJ), and Contrast Limited Adaptive Histogram Equalization (CLAHE). After preprocessing they used the models to determine the seriousness and probability of the disease. ResNet50 provides best accuracy of 78.64% on the original images. Dutta, et al. [14] used three DL models: a deep neural network (DNN), a convolutional neural network (CNN) and a feed-forward neural network (FNN) on publicly available Kaggle dataset. The total images were 35128, but (Dutta et al., 2018) used only 2000 images. They applied Median, Mean, and Std Deviation to the dataset in preprocessing steps and achieved 89.6% accuracy on the training dataset using DNN. Khan, et al. [15] Proposed a model where VGG-16 and network-in-network (NiN) are staked to create a profound model for detecting DR known as the VGG-NiN model. Due to the advantages of the spatial pyramid pooling layer and the stacking of NiN, which increases the model's nonlinearity and helps it perform better classification, the VGG-NiN model can handle DR images at any size. The model obtained an average F1-Score of 59.6%. The proposed model had a high F1-Score, or 94.0%, and could classify the Class 0 (No-DR) stage. Hemanth, et al. [16] developed a different hybrid model for using retinal pictures to diagnose diabetic retinopathy. Deep learning and image processing techniques are the foundation of the method. Histogram equalization and contrast-limited adaptive histogram equalization techniques are used in image processing. Additionally, CNN makes the DR diagnosis. The hybrid method was valid on 400 retinal images of Messidor database, and the evaluation parameters were obtained as accuracy 96%, F-1 Score 94%, and specificity 98%. Keel, et al. [17] commenced the initialization of a Deep Convolutional Neural Network (DCNN) for the purpose of recognizing diabetic retinopathy within retinal images. The utilization of deep learning within retinal fundus photographs facilitated the creation of an algorithm designed to automatically detect both DR and diabetic macular edema. Predicated on the principal assessments made by the team of ophthalmologists, the algorithm's ability to ascertain moderate or more severe DR, or a combination thereof, yielded specificities and sensitivities. The development of the algorithm was facilitated by employing extensive datasets with varying grades per image, harnessed through deep convolutional neural networks. As a result of these efforts, the model achieved a specificity and sensitivity of 92.4% and 96.5% respectively thereby showcasing its substantial potential in diabetic retinopathy detection and categorization. Novel deep learning hybrids have been proposed by Gangwar & Ravi [18] as a solution to the issue of automated diabetic retinopathy identification. They employed transfer learning to the pre-trained Inception-ResNet-v2 and built a precedent CNN block to develop the model. Their developed model was trained and tested using the APTOS-2019 and Messidor-1 datasets and the test accuracy was 82.18% and 72.33% respectively. Lifeng, et al. [19] developed a deep learning framework for detection of microaneurysms in color fundus images of people suffering from diabetes. This approach helps the ophthalmologist in timely and early-stage diagnosis of diabetic retinopathy. The model was based on deep learning principles and the algorithms of convolutional neural network were used for development of the model. Furthermore, the power of GPU (Graphics Processing Unit) was harnessed to speed up the process and thus producing the results in high performance. The proposed framework is utilized for semantic segmentation algorithms, which categorize the fundus images as either normal or infected.

The diabetic retinopathy research is divided into two primary groups. The first group is to classify the retinal images based on binary classification which determines whether a patient has DR or is free from the disease. However, this approach was limited as it cannot detect the severity of the disease. Solution to this limitation is proposed: the use of multi-class classification in which diabetic retinopathy is divided into five distinct categories. Unfortunately, many existing models failed to detect the five stages efficiently particularly the early stages. The DR detection in its early stages is crucial because treating the disease in later stages becomes challenging and the patient may suffer from vision loss. Therefore, the purpose of this research is to detect diabetic retinopathy in its early stage using Kaggle dataset.

Objectives:

The purpose of this study is to propose a deep learning densenet121 based model on a publicly available dataset comprising of color fundus images thus making it challenging for detection and classification. For development of the model the dataset is pre-processed first in which size reduction, splitting of data, data augmentation and feature enhancement processes are done for accurate detection and categorization of various phases of diabetic retinopathy. Then the deep learning model is hyper tuned in terms of batch size and learning rate and then it is trained on the dataset which was pre-processed in earlier stage as per the needs.

Material and Methods:

This study revolves around implementing and experimenting with a deep learning (DL) model, specifically the Dense Net 121 architecture. Dense Net 121, a sophisticated Convolutional Neural Network (CNN) design, is widely recognized for its dense connectivity structure, which promotes effective information exchange among layers. Its effectiveness has been demonstrated in numerous image classification tasks, making it particularly best for the aim of detecting and classifying Diabetic Retinopathy (DR). The block diagram is presented in Figure. 2. Shows the overall steps of the proposed model which are described in detail in the subsequent sections.

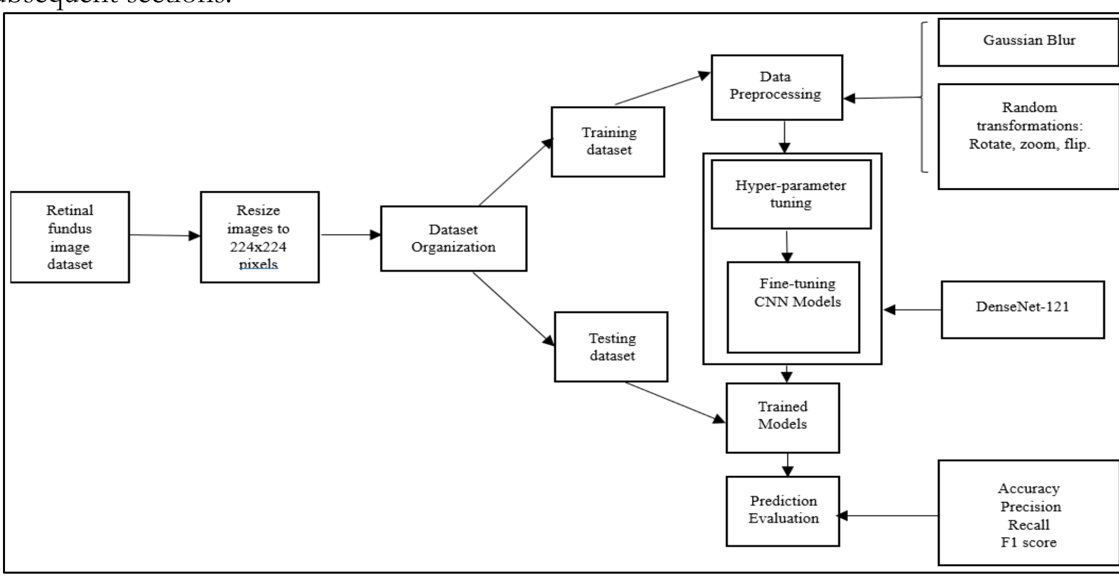

Figure 2: Various phases of Diabetic Retinopathy

Data Acquisition:

The proposed method has utilized the APTOS2019 dataset available on Kaggle. The given dataset is comprised of 5593 number of color fundus images, each assigned a severity level label ranging from 0 to 4, indicating the extent of the disease. The images are divided into 4 classes: No DR, mild, moderate, severe and NPDR. The No DR class comprises of 1805 fundus images. Mild class comprises of 370 fundus images whereas moderate class contains 999 retinal fundus images and severe class contains 193 images. The NPDR class comprises of 295 fundus images. This dataset was utilized for both training and testing the model. Out of 3847 number of images, 2804 images were employed for training phase and 494 images were used for validation purpose. However, 549 images are randomly selected for testing and evaluation purpose.

Data Processing and Augmentation:

After the image acquisition step, a preprocessing step has been carried out to remove the unnecessary information from the fundus images. To perform preprocessing first the black surrounding pixels are removed using simple cropping in python and then images are resized to the dimension of 224 x 224 to preserve the computational resources. Figure 3 illustrates a representative outcome of this image preprocessing applied to a randomly selected fundus image from the dataset described in the image acquisition section. Further, Gaussian blur has been applied to all the input images to enhance the DR features.

Figure 3: The result of preprocessing stage (a) original fundus image (b) preprocessed image

Gaussian filtering is a widely recognized technique used to eliminate noise from images, resulting in a smoother appearance which helps the model to focus on the relevant features such as microaneurysms, hemorrhages, and exudates. It is also used to preserve the edges of the fundus images so that the critical details should remain distinguishable even after preprocessing. Processing the model with gaussian blur can help the model to generalize better which means the model can perform better on unseen data leading to more reliable detection and classification of the disease.

After data preprocessing, another crucial step of data augmentation is carried out which is employed to address the imbalances between different classes of images, particularly useful when dealing with datasets characterized by significant class imbalances. Through image augmentation, images undergo transformations such as flipping, rotation, translation, or mirroring, generating additional instances of images for classes that are underrepresented in comparison to others. This helps create a more balanced and diverse dataset, enhancing the robustness and generalization capability of the model during training.

Model Training:

After the data is pre-processed, this section describes the training of the deep learning model, CNN-DenseNet121. A deep CNN's structure comprises of two fundamental components: a convolutional component and a classifier component. The convolutional component convolves with the input data, capturing distinctive features that differentiate various classes, while the classifier component categorizes the input data using the gathered features. This study makes use of DenseNet-121 model for extraction of DR features and SoftMax classifier for classifying various phases of diabetic retinopathy. The details of the DenseNe121 architecture is described in the given sub-section.

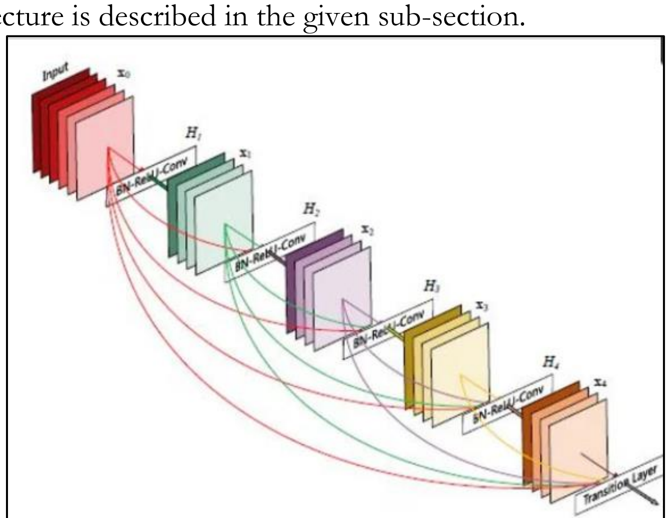

Figure 4: DenseNet121 Architecture

Dense Net121 Architecture:

Dense Net, a variant of convolutional neural networks (CNNs), facilitates the creation of deeper network structures by establishing connections in a feed-forward manner, linking each layer directly to every other layer. In the Dense net architecture, all the layers take inputs from the preceding layers to share the feature maps with all the successive layers and thus creating a dense pattern. Thus, this dense interconnection fosters effective information flow and encourages the reuse of features across the entire network. Figure 4 depicts the internal architecture of the Dense-121 model.

The architecture of Dense Net contains fundamental convolutional layers, dense blocks, pooling layers and transition layers. Initiating with a block of convolution possessing a sliding window of 7x7 dimension on the input image and then it generates 64 output filters for down sampling with a stride of 2. The feature map then undergoes a reduction through max pooling layer in spatial dimensions using a sliding window of 3x3 and a stride of 2. The convolution blocks follow a well-defined sequence in which they begin with standardization of batch normalization layer then adding nonlinearity with an activation function such as ReLU. Afterwards, using a Conv2D layer the architecture performs convolution process. This sequence is repeated 6 times in the first block of densenet121 architecture. In the second block it is repeated 12 times, Similarly, it is repeated 24 and 16 times in third and fourth dense block respectively.

The transition layers of the architecture are used for decreasing channel number in feature maps. These layers are located right after the dense blocks containing a convolutional layer of 1x1 following an average pooling layer of 2x2. This pairing systematically decreases the channel number by half from one block to the next. The channel count of densenet121 architecture successfully decreased from 256 channels to 32, first from 256 to 128 then 64 and finally 32 resulting in a fixed length representation of vectors. Finally, for classification purposes a fully connected layer with an activation function such as softmax in order to produce the probabilities of a class.

Hyperparameter Tuning:

This section describes the classification or categorization of various phases of diabetic retinopathy. The model was trained and tested for multiclass classification using scikit learn [18] and TensorFlow [17] libraries in python. Adam Optimizer [19] has been used to optimize the training process. Table 1 represents the setting of parameters that are used in the development of the model.

Table 1: Model Training parameters.

Densenet-121 Model	
Batch Size	16
Learning Rate	0.00005
Epochs	20

Inaugurating hyper parameters plays a vital role in the convergence and efficiency of deep learning models. In this study we observed the practices for setting hyper parameters and thus, aligning them with the specs of the selected model. Learning rate is a tunable parameter in neural network, which governs the weight updates extension in each iteration, which is commonly known as the step size. This parameter also serves for the gradients as a multiplies for calculation in backpropagation which impacts the speed and effectiveness. While a higher learning rate can be used to accelerate convergence, it carries the efficient solution. Contrarily, a lower learning rate is used to more accurate weight updates.

Another crucial hyper parameter is the batch size which dictates the processed quantity of samples before updating the model. The batch size defines the sections of data samples in each iteration which are utilized for gradients computation and adjustment of model parameters.

Selection of an efficient batch size requires a balance between computational efficiency and weight update quality.

Furthermore, the number of epochs creates the passes through the dataset in training phase. The model sets its weights by using computed gradients from the batched data when every epoch encircles multiple iterations. Deciding the epoch number joints the convergence pattern and targeted training level of the model. More intricate tasks or models might demand a higher number of epochs for convergence, whereas simpler tasks or models may achieve convergence more rapidly.

The selection of the batch size, learning rate and epochs for training the model was done based on a practical approach. The training of the model started from initiating a small batch size and a smaller number of epochs for say 10. Then gradually the number of hyper parameters were re-adjusted based on the results and the training was then iterated several times in order to reach the optimal selection as mentioned in table 1.

Result and Discussion:

Extensive experiments have been performed to check the performance of the proposed methodology. The experimental setup included a PC with 64-bit Windows operating system, and 8GB RAM. The assessment of the model has been conducted using the accuracy metric, defined by equation (1),

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

The APTOS dataset served as the training and testing grounds for the model, with 80% of the data allocated to training and the remaining 20% for testing. The training process unfolded across 20 epochs. The model attained a commendable overall accuracy of 90%. Figure 5 represents the accuracy and the loss of the model graphically. It may be noted that Figure. 5(a) represents the progression of the loss function over the given training epochs with the x-axis corresponds to epochs, and the y-axis represents the corresponding loss values. A descending trend in the graph depicted by Figure. 5(a) indicates that the model is improving its performance, ultimately converging towards a state of minimized loss, reflective of enhanced predictive accuracy.

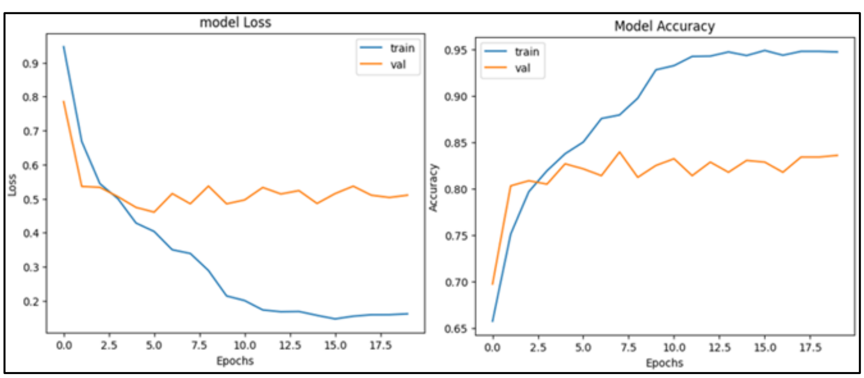

Figure 5: (a) Model Loss (b) Model Accuracy

Additionally, it can be observed that Figure. 5(b) depicts the graph of the model accuracy which visually captures the performance evolution of a machine learning model during training. Initially, the model's parameters, such as weights and biases, are initialized. By looking at the graph in Figure. 5(b) it is quite clear that through successive training epochs, the model undergoes a forward pass, processing input data to generate predictions. Simultaneously, the accuracy of these predictions concerning the actual target values is computed. This accuracy metric signifies the proportion of correct predictions made by the model. The model adjusts its parameters during a backward pass (backpropagation) to enhance accuracy, typically using optimization algorithms like gradient descent. The iterative nature of this process is reflected across the x-axis of the accuracy graph, with each point representing an epoch, while the y-axis denotes the corresponding accuracy values. An increasing trend shown in the graph shows that the model is improving its capabilities of prediction over time. An accuracy graph indicates the higher accuracy of the model.

In Figure. 5(b) the graph of model accuracy visually represents the machine learning model performance during its training phase. Firstly, the parameters of the model are initialized such as weights and biases. After that through successful training of epochs the model goes into a forward pass where the model processes the input data to generate the predictions. At the same time, the model computes the accuracy of these predictions regarding the actual target values. The model adjusts its parameters during a backward pass (backpropagation) to enhance accuracy, typically using optimization algorithms like gradient descent. The iterative nature of this process is reflected across the x-axis of the accuracy graph, with each point representing an epoch, while the y-axis denotes the corresponding accuracy values. An ascending trend in the graph indicates that the model is improving its predictive capabilities over time. A well-defined accuracy graph illustrates the convergence of the model towards higher accuracy, reflecting its learning progression and ability to make more precise predictions as training unfolds. Figure. 6 shows the confusion matrix of the proposed model which provides a detailed overview of the classification and shows the exact number of true positives, false positives, true negatives, and false negatives.

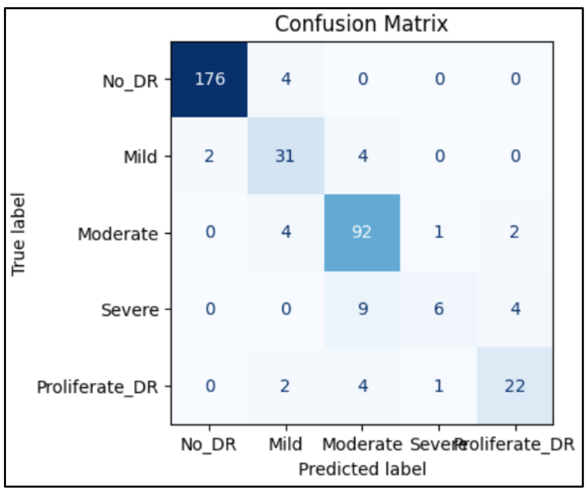

Figure 6: Confusion Matrix

Classification Report:

	precision	recall	f1-score
0	0.99	0.98	0.98
1	0.76	0.84	0.79
2	0.84	0.93	0.88
3	0.75	0.32	0.44
4	0.79	0.76	0.77
accuracy			0.90

Figure 7: Classification report of the model

Figure. 7 provides the statistical analysis of the proposed model resulting from the confusion matrix shown in Figure. 6. In Figure. 7 the 0, 1, 2, 3 and 4 indicate the classes of diabetic retinopathy which are No DR, Mild, Moderate, Severe and PDR. The precision ratio of true positive to all predicted positives, of each class of diabetic retinopathy is given as 99%, 76%, 84%, 75% and 79% respectively.

Similarly, the recall, ratio of true positives to all actual positives, and F1 score, a harmonic mean of precision and recall are also given in Figure. 7. To check the effectiveness of the proposed model, a fair comparison has been provided in the Table 2, where the effectiveness of the proposed model has been assessed by comparing its performance with several existing methods with different deep learning models namely VGG, Inception Resnet V2, Inception V3, CNN. However, it can be observed that this study has provided a comparison only with those existing methods which have used the same dataset, APTOS, as employed by this study so that a fair comparison can be made.

Table 2: Comparative Analysis

Paper	Dataset	Architecture	Accuracy
[4]	APTOS	Dense121	80.08%
[15]	APTOS	VGG	85.0%
[18]	APTOS	Inception Res Net V2	82.18%
[20]	APTOS	Inception V3	82.0%
[21]	APTOS	CNN	75.61%
Proposed	APTOS	Dense121	90.0%

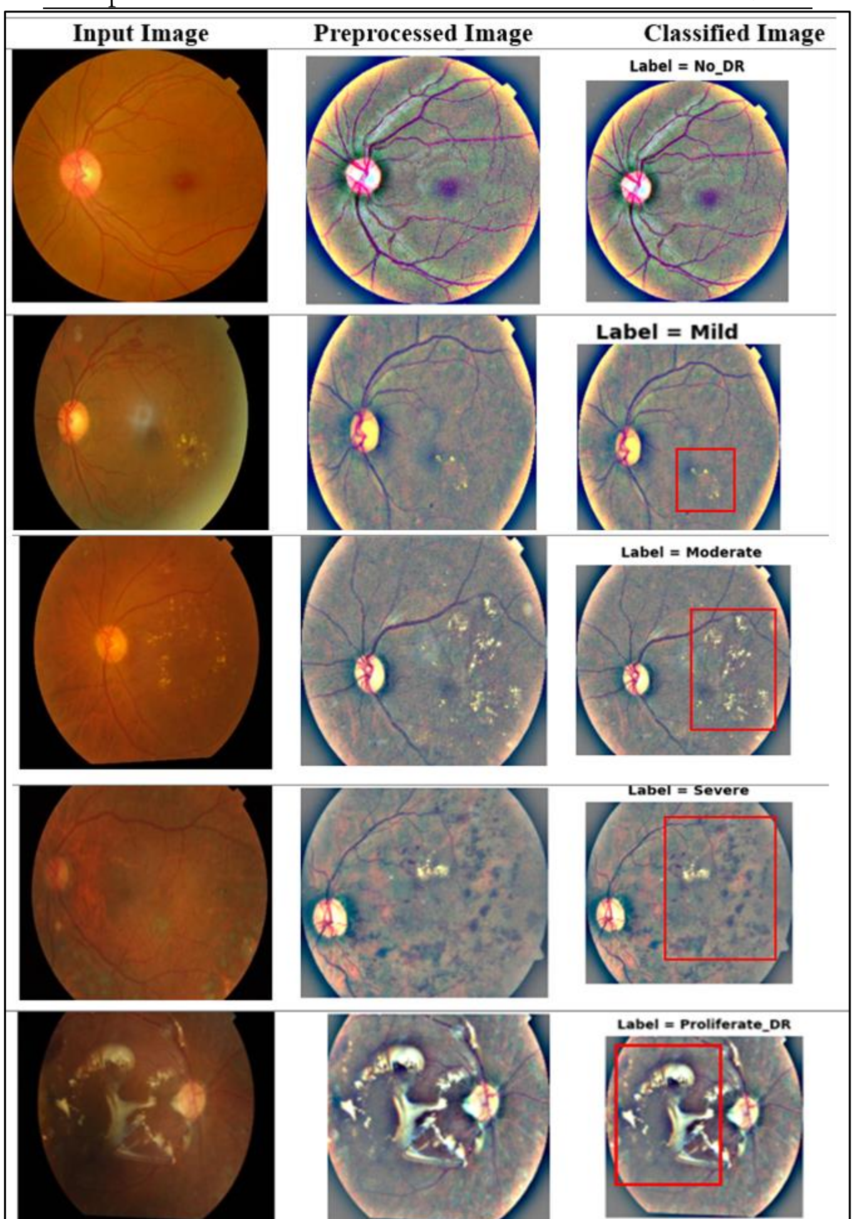

Figure 8: Classification results using DenseNet121 (a) Input images (b) Preprocessed Images (c) prediction with severity level including No-DR, Mild, Moderate, Severe, Proliferate (PDR).

Notably, the proposed model outperformed other techniques on the APTOS 2019 Blindness Detection dataset, achieving a superior accuracy score of 90%. This is due to the reason of the dense connectivity pattern. Due to the dense connectivity pattern of densenet121 model the proposed model gave higher accuracy as compared to others because it allows efficient propagation of information through the network which allows the model to acquire and use main features from each preceding layer which results in efficient and accurate predictions. However, the proposed model was trained for binary classification first which only predicts whether the disease is present or not and then it further classifies the disease according to the severity of diabetic retinopathy.

It can be observed that Qummar, et al. [4] have also used Dense121 for their model development but they got an accuracy of 80.08% which is relatively low as compared to the proposed model. However, the datasets used in both the models are the same. The proposed model gave higher accuracy because the model was first trained for binary classification which only detects whether the DR is present or not in the input images and if the DR is present then the model is trained for multi-class classification in order to categorize various phases of the disease. Due to this division of the problem the model was successfully able to give accuracy of 90%. However, Qummar, et al. [4] trained the model directly for multi-class classification which fails to detect early stages efficiently.

Since, it is not possible to show the results for the whole data set visually. Therefore, we have randomly selected five images to represent each of the DR-stages visually. The qualitative results of the classification for these selected images using proposed deep learning model, DenseNet121, are represented in Figure. 6. The overall Figure. 8 is comprising of three columns, the first column represents the input images, the second column represents the preprocessed images, and the third column shows the result of classification with a bounding box exhibiting different stages of mild, moderate, severe, and proliferate, respectively. It can be noted visually that in all of the images the proposed method has made an accurate prediction along with the severity level that in all of the images the proposed method has made an accurate prediction along with the severity level.

Conclusion:

Diabetes has become increasingly prevalent in recent times, and research indicates that individuals with diabetes face approximately a 30% risk of developing Diabetic Retinopathy (DR). DR is characterized by a range of phases, from mild to severe, and PDR (Proliferative Diabetic Retinopathy). In its advanced stages, this condition can manifest as floaters, blurry vision, and ultimately, if not identified in its early phases, it can lead to blindness. The manual diagnosis of DR images demands the expertise of highly trained professionals, is time-intensive, and poses significant challenges. To address these challenges, various computer vision-based methods are outlined in literature. In this paper, our primary focus is on classifying all stages of DR, with particular emphasis on the early stages, which represent a significant limitation in existing models. To achieve this, we introduce a DenseNet-121 model designed to detect and categorize the various stages of DR in color fundus images. For training and evaluating our model, we utilize the largest publicly available fundus image dataset, obtained from Kaggle. The results showed that our model outperforms other existing methods and excels in detecting all stages of DR. Looking ahead, we plan to enhance the accuracy of early-stage detection by training dedicated models for each specific stage and then combining their outcomes.

Acknowledgement: The writers express their gratitude to Mehran University of Engineering and Technology, Jamshoro, and Quaid-e-Azam University of Engineering, Science, and Technology, Nawab Shah for lending us the tools required to carry out this study.

Author's Contribution: Every author has contributed equally to this research.

Conflict of Interest: The authors declare no conflict of interest in publishing this manuscript in IJIST.

Project Details. Nil

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