Deploying Efficient Net (BNs) for grading Diabetic Retinopathy severity levels from fundus images

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ISLAMABAD

JANUARY, 2023

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A thesis submitted in partial fulfillment of the requirements for the degree of MS Biomedical Sciences

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Signature of Student______________________

SUMMIYA BATOOL

2019-NUST-MS-BMS-317532

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Dedication

Dedicated to my grandparents '**Nani Ami & Nana Abbu'** for being a beautiful memory of my childhood. May Allah always keep you smiling in your next life Ameen!

Acknowledgements

I'm grateful to my Creator, Allah Subhana-Watala, for guiding me through every stage of my effort and for each fresh idea You planted in my head to make it better. Indeed, without Your invaluable assistance and direction, I would have been powerless.

It was Your will that everyone who assisted me with my thesis, including my parents and others, thus only You are deserving of recognition. I am incredibly grateful to my wonderful parents who reared me when I was unable to walk and who have supported me throughout my life in every aspect.

Additionally, I want to give a particular thank you to my thesis advisor, Dr. Syed Omer Gilani, for his guidance throughout the writing of my thesis and for teaching me Python and Fastai. I can confidently claim that none of the engineering topics he has taught have been covered in as much detail as those that he has. Additionally, I would like to express my gratitude to Dr. Asim Waris and Dr. Fahad Iqbal for their outstanding assistance and cooperation. They always had a solution when I got stuck on something. Without their help, I wouldn’t have been able to complete my thesis.

I appreciate his patience and guidance throughout the whole thesis. I would also like to thank my friends Ramsha Abbasi and Saba Anwer for being on my thesis guidance and evaluation committee and express my special thanks to Dr. Amer Kashif for his help. I am also thankful to all my teachers for their support and cooperation. Finally, I would like to express my gratitude to all the individuals who have rendered valuable assistance to my study.

Abstract

One of the common and escalating endocrine illnesses is diabetes mellitus. Diabetic retinopathy is a common eye problem in patients with diabetes. Diabetic retinopathy (DR), a retinal condition, is acknowledged as an epidemic on a global scale. One-third of the estimated 285 million persons with diabetes show symptoms of DR, and one-third of them have DR that threatens their vision [1]. In addition, the figures are rising. By 2040, 288 million individuals are expected to have AMD, and by 2050, the number of people with DR is projected to treble. The need for reliable diabetic retinopathy screening systems became a critical issue recently due to the increase in the number of diabetic patients. The severity of DR can be graded into five stages: normal, mild NPDR, moderate NPDR, severe NPDR, and PDR. Early diagnosis and treatment of DR can be accomplished by organizing large regular screening programs. Numerous Convolutional neural network models are developed for the diagnosis of DR in fundus images using deep learning methods. In Deep Learning (DL) one of the methods is a computer-aided medical diagnosis for the detection of DR. There are many DL-based methods such as restricted Boltzmann Machines, convolutional neural networks (CNNs), auto-encoder, and sparse coding. On the other hand, it is thought-provoking to distinguish it initially not display signs in the initial classes. The current models for diabetic retinopathy mayn't identify entire classes of DR. The utmost commonly used metrics like accuracy, f1-score, precision, and recall; do not cogitate the standard of difference among labels, which supports spotting all classes of DR. In our paper used Efficient Net BNs models. We concluded evaluation scores using the F1-score, which is applicable for grading various classes of DR established on the intensity levels. We have accomplished the F1- score of 0.88 and 0.84 using the simple preprocess, Gaussian smoothing filters, and deploying an Efficient Net BNs network on DeepDRiD and EYE-PACS datasets.

Key Words: *diabetic retinopathy (DR), Deep learning (DL); Non-proliferative Diabetic Retinopathy (NPDR); Proliferative Diabetic (PDR); Efficient Net BNs; F1-score; Convolutional neural network*

Contents

List of Figures

List of Tables

Abbreviations

DR	Diabetic Retinopathy
CNN	Convolutional Neural Network
DL	Deep Learning
NPDR	Non Proliferative Diabetic Retinopathy
PDR	Proliferative Diabetic Retinopathy
ML	Machine Learning
AI	Artificial Intelligence

CHAPTER 1: INTRODUCTION

The research work in this dissertation has been presented in two parts. First part is related to the data distribution discussion. The objective of this part is to study grading of diabetic retinopathy classes. The second part includes the preprocessing, data augmentation, and model training.

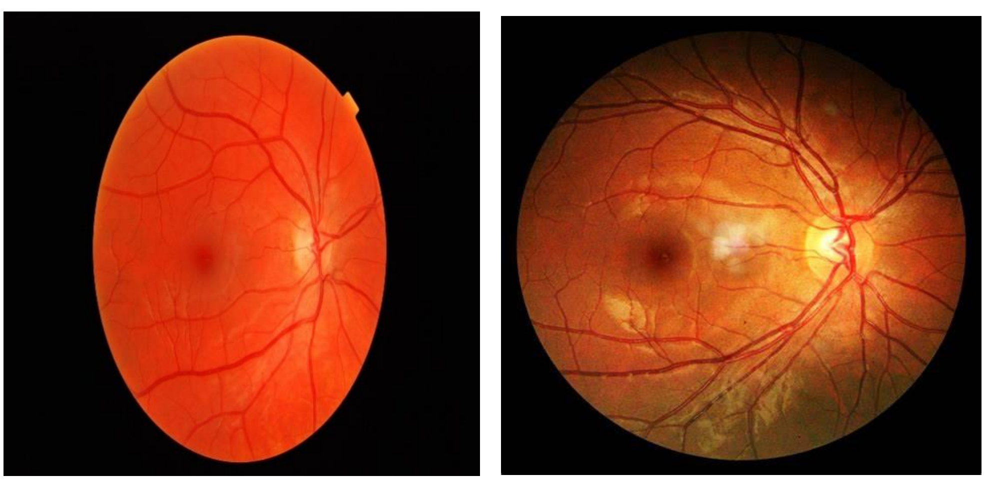
1.1 Diabetic Retinopathy

A diabetes condition that impacts the eyes is diabetic retinopathy. Damage to the blood vessels in the light-sensitive tissue at the back of the eye is what causes it (retina). Initially, diabetic retinopathy may not manifest any symptoms or may only result in minor vision issues. But it might result in blindness. Any person with type 1 or type 2 diabetes has the potential to acquire the illness. The likelihood of developing this ocular problem increases with the duration of diabetes and the degree of blood sugar management. DR is a worldwide diabetic eye disease and a major cause of blindness. In diabetic patients increment of blood sugar level causes breakage of the tiny blood vessel in the retina and leads to hemorrhage in the retina. The intensity of disease varies from normal vision to complete vision loss (G. Jinfeng et al., 2020). A number of major health issues are more likely to occur if you have diabetes mellitus. Microvascular problems, which result from harm to small blood vessels, are one category of these issues. Damage to larger blood arteries causes macro-vascular conditions (WHO). Micro vascular problems can affect the eyes and cause retinopathy, which can cause blindness, the kidneys and cause nephropathy, which can cause renal failure, and the nerves and cause neuropathy, which can cause impotence. Ophthalmology and other medical specialties that have utilized artificial intelligence (AI), machine learning (ML), and deep learning have a lot in common because they both involve complicated diagnostic imaging, which is the most well-known use of AI in healthcare (Muhammad Kashif Jabbar et al., 2022). Artificial intelligence in medicine has several benefits. The intricacy of 21st-century ophthalmology lends itself particularly well to the use of artificial intelligence, which can assist clinical practice by applying effective algorithms to detect and forecast aspects of imaging data. Errors in diagnosis and treatment are lessened. Additionally, AI, ML, and deep learning can identify patterns associated with particular diseases and link unique features to provide ground-breaking scientific discoveries. According to recent data, 463 million individuals worldwide have diabetes, and one-third of these patients have diabetic retinopathy of some degree. Thus, there are currently about 160 million diabetic people who have diabetic retinopathy, and it is predicted that number would rise to 191 million by 2030 (Muhammad Kashif Jabbar et al., 2022).

1.2 Symptoms

During the early stages of diabetic retinopathy, you might not experience any symptoms. As the situation worsens, you could get:

- Spots or dark strings floating in your vision (floaters)
- Blurred vision
- Fluctuating vision
- Dark or empty areas in your vision
- Vision loss



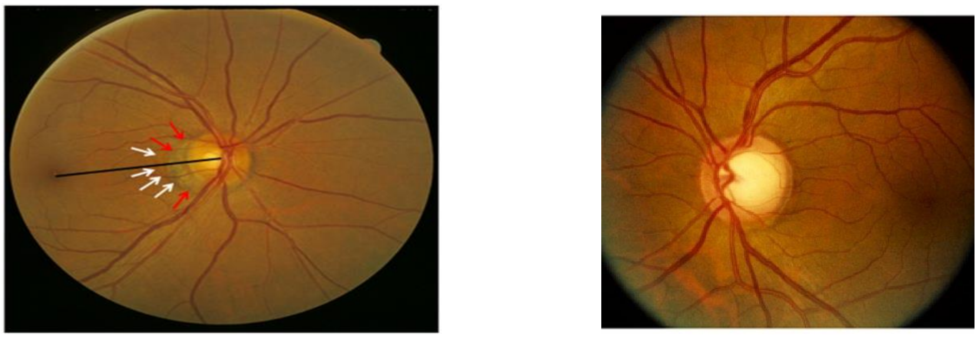
(a) (b)

Figure 1. 1 (a) Normal Eye fundus Image (b) PDR Eye fundus Image

1.3 Classes of Diabetic Retinopathy

Diabetes mellitus is a chronic condition that constantly evolves (Douglas Abreu da Rocha et al., 2022). In the early stages of conventional DR, we might not notice any symptoms or just experience a small amount of vision loss. Ultimately, blindness results from delayed diagnosis and treatment. According to the progression of the disease, DR is typically divided into three groups: normal, non-proliferative DR (NPDR), and proliferative DR (PDR).

The wall of blood vessels has disappeared and no new retinal blood vessels are growing in NPDR. NPDR can be classified as mild, moderate, or severe. New blood vessels in the retinal region obstruct the retina's ability to receive blood during the PDR stage (G. Jinfeng et al., 2020). The risk of developing blindness must be reduced by diagnosing the DR at the earliest possible stage. Many researchers have proposed various computer-aided intelligent identification methods in the last ten years. The diagnosis of sickness requires careful observation, several tries, and is not always accurate with the naked eye. The computer-aided diagnostic methodology is more effective than traditional detection methods and saves money and time. The current study evaluates deep learning-based automated DR detection and classification algorithms (Islam et al., 2022). For the automated diagnosis of DR, some researchers have designed a number of machine-learning and deep-learning problem-solving methods (Islam et al., 2022). The goal of our current work is to create an automated system that can I read and visualize all photos from data and (ii) categories all grades according to the degree of DR severity. It took a long time to categorize the various stages of DR in the previous decade because the available networks needed complex procedures and steps. We classify DR phases using straightforward, lightweight CNN-based models. These models don't require a lot of time or complexity (Huynh et al., 2022). For the DR-restricted strength of training data images and variable annotations, computer-aided diagnosis systems have recently encountered two additional challenges (Saranya et al., 2020). An open-source framework for deep learning in medical imaging is built on MONAI PyTorch and uses the effective neural network model. In our paper, we used Efficient Net BN Models to classify five stages of diabetic retinopathy (Zhou et al., 2020). The dataset includes each eye's dual-view images (the optic disc as the center and the fovea as the center). A depression in the inner retinal surface where eyesight is the sharpest know as Fovea. The circular area in the back of the inside of the eye where the optic nerve connects to the retina and it also called the optic nerve head. Both are displayed in the below figures.



(a) (b)

Figure 1. 2 (a) Fovea as a center and (b) Optic disc as the center

The fundus images Fovea or Optic disc as the center are visible in above figures of fundus image of eyes.

CHAPTER 2: RELATED WORK

The CNN (Saranya et al., 2020) deployed layers were assessed on two online available databases and these are MESSIDOR and IDRiD. They classified four classes (0, 1, 2, 3) of diabetic retinopathy and they did not use PDR (4) stage. They applied a preprocessing technique in their model which was simple and that did not need extensive and complex processing. The (Gao Jinfeng et al., 2020) two deep CNN models used an ensemble method to detect all the DR stages by using balanced & unbalanced datasets. The outcome demonstrated that models outperform more sophisticated techniques like the Kaggle datasets in contrast to how well they now detect all stages of DR. By implementing a light-weight mobile network and assessing the effectiveness of their classifier, (SARAH SHEIKH et al., 2020) employed a novel approach. MobileNetV2 was constructed as a lightweight, mobile-friendly architecture and trained using datasets of diabetic retinal fundus images. In the paper (San-Li Yi et al., 2021) applied RA-Efficient Net for 2-grade and 5-grade classifications. They used APTOS 2019 dataset. In their model RA block best to perceive between the lesion features of DR images. The VGG Net model grade 5 classes and an additional grade (class 5) were applied by Douglas Abreu da Rocha et al. [3] to reveal the poor quality of digitized retinal images that are frequently found online and available in the DDR, EyePACS, and IDRiD databases. In accordance with (G. Jinfeng et al., 2020) proposed work, methods using fundus pictures and the VGG-Net were combined to enhance classification performance. The effective preprocessed techniques used were non-local mean denoising for improved retinal picture viewing, weighted Gaussian blur, and interpolation scaling of images. A new method for binary class and multiclass classification based on the datasets of APTOS (2019) blindness detection & Messidor-II was announced by (Md. Nahiduzzaman et al. 2021). Initially, data were preprocessed by applying Ben Graham's technique. To locate the contrast-enhanced image data with the least amount of noise, contrast-limited adaptive histogram equalization (CLAHE) has been used. After that, a new hybrid CNN model singular value decomposition is proved to be useful for decreasing the input classifier. To reduce the training time, an ELM technique was employed as the classifier. Their approach focused on accuracy, precision, recall, and F1 score, showing the achievable potential of a future DR detection strategy. The applied depth learning-based ensemble techniques for diabetic retinopathy identification (Khan et al., 2021). They conducted structural modifications in real CNN to increase the effectiveness and precision of grading the DR's classes in fundus colorful images. They worked on an imbalanced Kaggle dataset to check the working of their deployed model. The results showed that the applied model did not have high accuracy computational scores. In (Sai Venkatesh Chilukoti et al., 2022) paper deployed ResNet, VGG, and Efficient Net BNs (0-6) models. They got results evaluation using the F1 and quadratic weighted kappa scores, which were suitable for grading various classes built on the intensity. But they got the best F1 and Quadratic weighted kappa scores on Efficient Net B3. In their paper noticed ResNet and VGG models evaluate least F1 & Quadratic weighted kappa = 0 scores. Our proposed work on Efficient Net BN (0-6) on two datasets evaluated the F1 score. We had improved the F1 score in all Efficient Net BNs but only Efficient Net b-3 has the same score in the EYE-PACS dataset as in previous work. For the first time evaluated the F1 score by applying Efficient Net BNs on DeepDRiD. Literature that studied during research work are mentioned in tabular form.

Title	Authors & publication year	Datasets	Models
A Benchmark for Studying Diabetic Retinopathy: Segmentation, Grading, and Transferability	Yi Zhou, IEEE Member, Boyang Wang, Lei Huang, Shanshan Cui, and Ling Shao, November-2020	FGADR dataset	VGG-16, Inception v3, DenseNet
Learning Discriminative Representations for Fine-Grained Diabetic Retinopathy Grading	Li Tian, Liyan Ma, Zhijie Wen, Shaorong Xie, Yupeng Xu 2021	IDRiD, DeepDRiD, FGADR dataset	DSOD (MULTI-SCALE FEATURE EXTRACTOR)
Automatic detection of non-proliferative diabetic retinopathy in retinal fundus images using convolution neural network	P. Saranya, S. Prabakaran September-2020	MESSIDOR, IDRiD	Simple CNN layer model
Diabetic Retinopathy Detection using Transfer Learning from Pre-trained Convolutional Neural Network Models	Sai Venkatesh Chilukoti, Dr. Anthony S Maida, and Dr. Xiali Hei 2022	EYE-PACS	Efficient net bns

Table 2. 1 Research Information Chart about different Dataset on CNN models

Here in this chart we added basic information of few studies of recent time between 2020 to 2022.

CHAPTER 3: METHODOLOGY

Our proposed framework includes the following phases: images into separate labels folders, data loading splitting train, validation & test data, preprocessing, data augmentation, and classification. Below is the figure of our proposed framework.

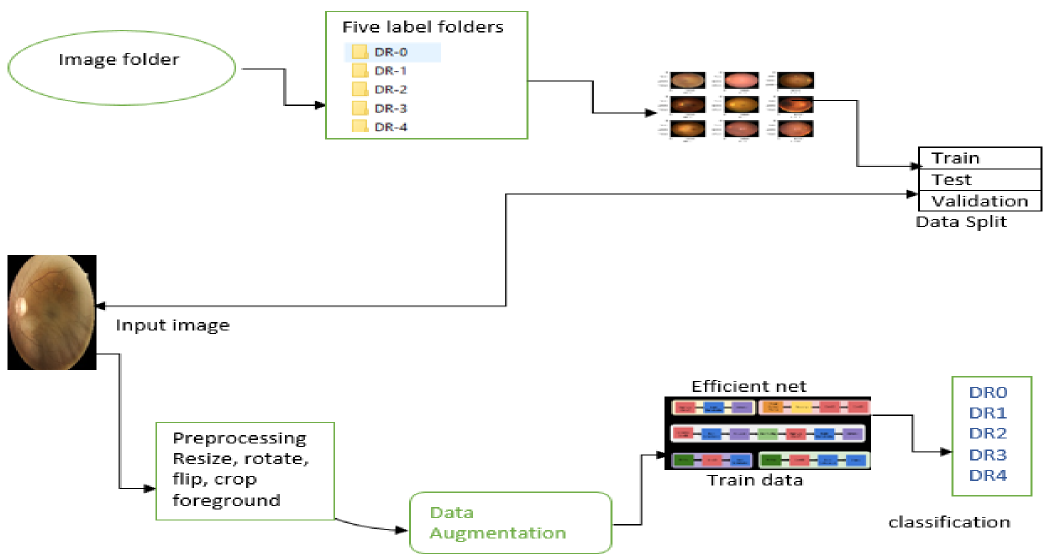


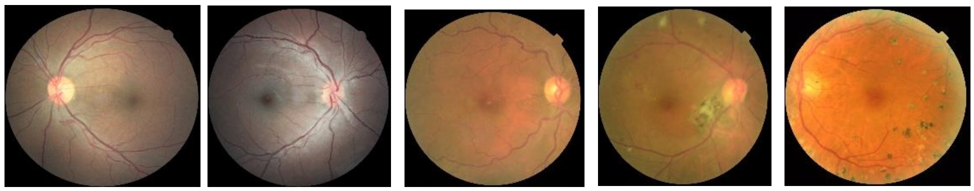
Figure 3.1 Our Framework for grading of diabetic retinopathy classes

Above framework describes how we graded our datasets. We followed these steps through which we got desired results. Here all the processes are mentioned through which more accurate test score was observed.

3.1 Description of Datasets

With the help of retinal fundus images, our work presents a predicate technique for grading DR. DeepDRiD and Kaggle EYE-PACS datasets, both of which are freely accessible online, are used. The total labeled fundus images in DeepDRiD and Kaggle datasets are 1600 and 35108. Compared to Kaggle EYE-PACS, DeepDRiD has a limited database. These two databases each feature five DR phases, which are represented by the numbers

0, 1, 2, 3, and 4: normal, mild, moderate, severe, and proliferative. Figure 2 displays fundus pictures of these five stages.



(i) (ii) (iii) (iv) (v)

Figure 3.2 Fundus Images (i) Normal (ii) Mild-DR (iii) Moderate-DR (iv) Severe-DR (v) PDR

The five DR-Stages are classified on the base of lesions. That is shown in the below table

Stages	Findings
No DR	No lesions or spots
Mild DR	multiple hemorrhages and cotton-wool spots
Moderate DR	presence of micro-aneurysms, intra-retinal hemorrhages, or venous beading
Severe DR	affecting small blood vessels in the eye due to blockage or leakage
PDR	retina starts growing new blood vessels

Table 3. 1 DR-Stages on the base of lesions

All image data is distributed into 5 different folders. Each folder has single label graded images. The data distribution is mentioned in the below table.

Labels	EYE PACS	DeepDRiD
No DR (0)	25802	714
Mild DR(1)	2438	186
Moderate DR(2)	5288	326
Severe DR (3)	872	282
PDR (4)	708	92
Total	35108	1600

Table 3. 2 Data Distribution of DR Five Labels on two data sets

Above table is describe the quantity of images in each class of two datasets (EYE-PACS & DeepDRiD). Normal Eye images are high in number and PDR images are least in number.

3.2 Separation into folders:

DeepDRiD has combined images of all grades into two folders. The first training folder has 300 patients' sub-folders and the second validation folder of 100 patients' sub-folders. With these folders two labeled CSV files are present. In each sub-folder, there are four eye images (2 left & 2 right). And Kaggle dataset has also one folder and a single CSV file. The folder has 35108 fundus images. We have used code to divide single image folder data into 5 separated label folders with the help of a given CSV file. We can distribute all fundus images into label folders in a very short time through code otherwise manually it will take too much time without knowing distribution into the following folders are correct or not.

3.3 Data Loading:

The data is set in the directory. The folders' paths are given in the directory. Firstly, read the dataset files and display some statistics. To train the classification model, the dataset's five folders—DR0, DR1, DR2, DR3, and DR4—should be tagged. Images from the dataset that were viewable were randomly selected. Create training, testing, and validation datasets from the data. Images are shown in the data loader:

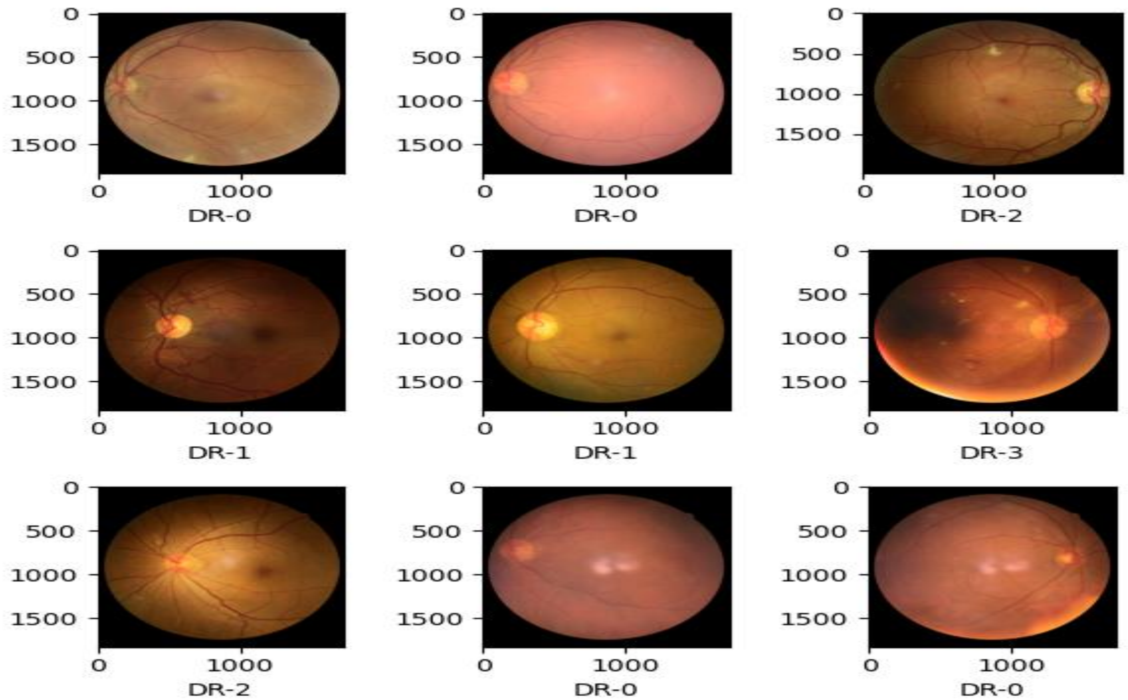


Figure 3.3 Data Loader of data images of all five classes of diabetic retinopathy

3.4 Preprocessing:

Preprocessing is the procedure that we apply before utilizing the data images for neural network training. In preprocessing we resize all image data in the same size, assess the distribution among the classes, and examine the visual quality of all classes. The preprocessing transforms are defined before adding them to data loaders. Compose Transform uses to order a series of callable collected in a sequence. Every transform in the series essentially takes only an argument and back to one value. In our proposed model we use simple and few preprocessing techniques. In preprocessing we applied the following transforms. These are mentioned below:

3.4.1 Crop Foreground:

We have applied the Crop Foreground transform to manipulate images. We have isolated the foreground and all black pixels everywhere else. After it, we are enabled to crop the image so there are no full black rows above and below, or full black columns left and right of the foreground. That can be shown in below figure.

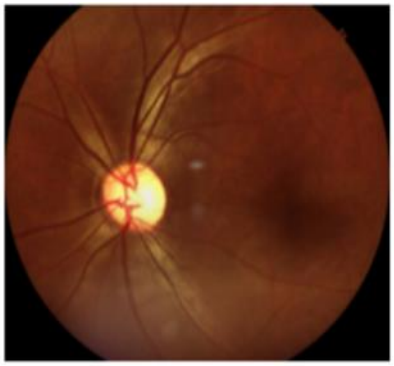


Figure 3. 4 Cropped Fundus Image

3.4.2 Resize:

We are using two different types of datasets, and both have different numbers of fundus images. These datasets have contrary image resolutions. In the Kaggle EYE-PACS dataset, the images have (1024, 1024) resolution. It is a huge dataset that's why for speeding up the training we resized the images (356, 356) resolution. And in DeepDRiD images have (1956×1934) resolution we resized the images to (512, 512) resolution. We haven't used too much complex preprocessing methods. And resizing image data is the main transform. After resizing images, we observed speedy and prominent changes in training. Eye image after resizing is shown below figure.

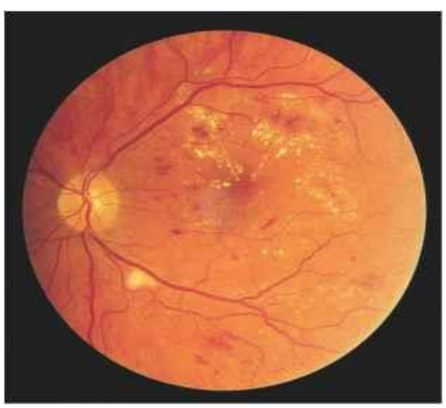
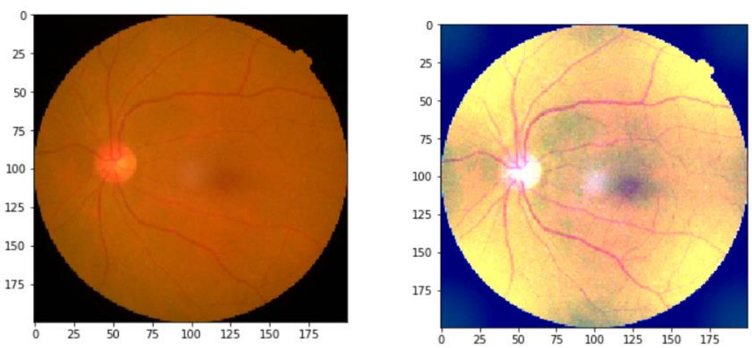


Figure 3. 5 Resize image

All fundus images in both datasets had various image resolution so we resized all images by applying resize transformation during preprocessing datasets.

3.4.3 Gaussian Smooth:

There is a noise in image data. We have overcome the noise by applying a filter. During preprocessing of the data, we used the Gaussian Smooth filter. Gaussian Smooth Filter (Gaussian blur) is a low pass filter applied for lowering the noise (high freq. components and distorting areas of data images). It is applied as an Odd sized Symmetric Kernel which is distributed over individual pixels of the ROI-Region of interest to develop the wanted effect. Gaussian filters are commonly isotropic, that is, they have exactly similar standard deviations along both dimensions. So, this filter removes extra noise from image data. After using this filter, we have observed a prominent effect on evaluation scores. We can be seen image result after applying Gaussian blur or Gaussian smooth in below figure after applying on image.



(a) (b)

Figure 3. 6 (a) Image before applying Gaussian Smooth filter and (b) Image after applying Gaussian Smooth filter

The Gaussian filters were used in preprocessing and data augmentation process to reduce noises in datasets. These filters helped to vivid the data more clearly.

3.5 Data Augmentation:

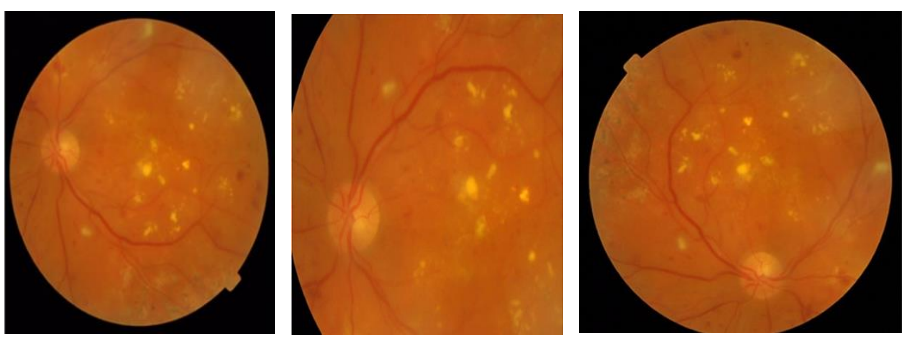
DL mostly track a problem where data images have a specific size. To obtain improved generalization in the model we require more data and so as many changes as likely in the images. Occasionally dataset is not sufficient to detect adequate variation, in such scenarios, we need to create additional data from a certain dataset. In such cases, augmented data can play a significant role.

This technique is used to artificially grow the size of the training set by generating modified data from the initial one. Data augmentation transforms are applied on each grade to avoid data misbalancing. By this technique, we can prevent overfitting & good for enhancing the model's performance and decreasing the number of false positives.

The transforms used in data augmentation are mentioned below:

- RandRotate (range_x=np.pi / 12, prob=0.50, keep size=True)
- RandFlip (spatial axis=0.0, prob=0.50)
- RandZoom (min zoom=0.90, max zoom=1.1, prob=0.50)
- Rand Gaussian Sharpen (prob=0.5)

Above all, these image augmentation methods have made the model more long-lasting and generalizable to poor-quality images. There following Flipped, zoomed and rotate fundus images of eyes are mentioned in below figures.



(a) (b) (c)

Figure 3. 7(a) Flip Image (b) Zoom Image (c) Rotate Image after applying data augmentation transforms

In these images augmentation transforms were applied and here transforms applied on one image showed who these transforms on all datasets. After data loaders preprocessing and augmentation of all data before data was going to training. The outline of preprocessing and augmentation are shown in below block diagram figure.

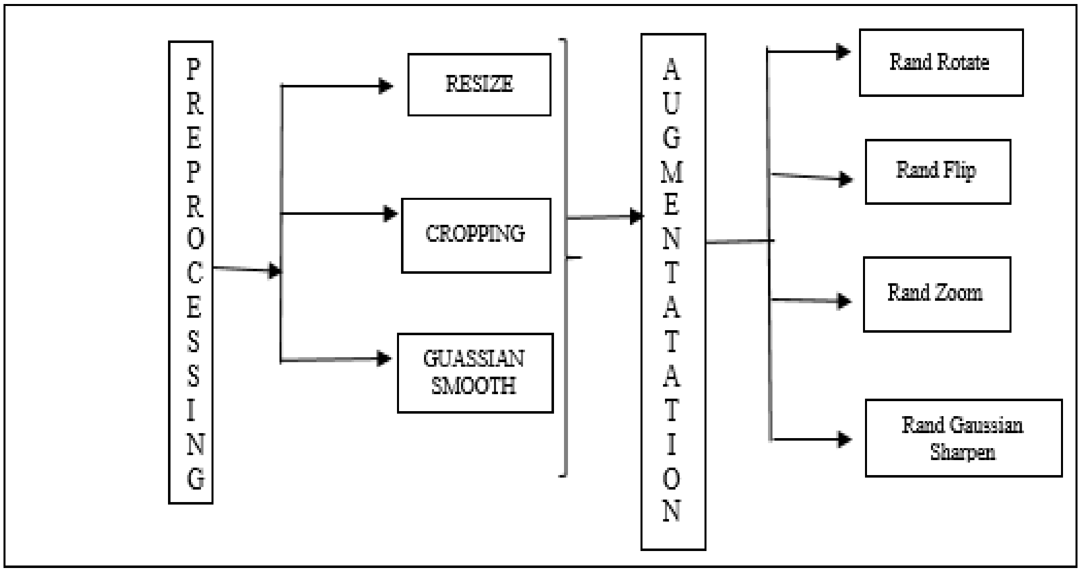


Figure 3. 8 Flow Chart of Preprocessing & Data Augmentation

3.6 Network structure:

There are numerous CNN models being used to classify the DR classes. Efficient Net appears to have performed admirably. This is because, in contrast to scaling techniques that arbitrarily scale depth, height, and breadth, a constructive scaling approach is used to increase the resolution, depth, and width of the images used in the architecture of the Efficient Net. Efficient Net is one of them which gives high accuracy scores with fewer parameters than other models that have high parameters. In the paper (Tan et al., 2019), Mingxing Tan and Quoc V. Le of the Google Research, Brain team introduced the Efficient Net categorization model. In order to create an autonomous network of neural networks that mutually optimizes accuracy and efficacy measured in FLOPS—floating point operations per second—they first created a network by carrying out a neural architecture search. This classification model's design customs the mobile inverted bottleneck convolution (MBConv). After that, researchers expanded the fundamental network to create the Efficient Nets deep-learning classifiers. Before model scaling was not changed layer operators in the baseline network, having a good baseline network is similarly serious. In addition to learning a new mobile size baseline called Efficient Net, we are computing such a scaling approach using real Conv-Nets, which better reflect the competency of the scaling strategy. The effectiveness of network scalability will be greatly influenced by the initial network used. In order to follow the AutoML MNAS framework, which aims to compute accuracy and efficiency, the architecture used as the baseline model on EfficientNet is called EfficientNet-B0 (FLOPS). The basic network is then built up using the compound scaling principle to create the family of Efficient Nets, which includes EfficientNet-B1 through EfficientNet-B7. The EfficientNet-B0 algorithm used in this study requires a mini-input size of 224 × 224 before the image size in the RMFD is smaller than 200 x 200 pixels [16]. Each Efficient Net Bn has five following modules.

The first module is utilized as the foundation for the subsequent blocks.

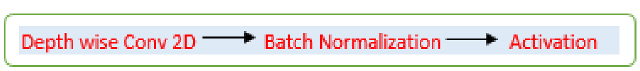
All seven of the main blocks, with the exception of the first, use Module 2 as their starting point for the first sub-block.

All of the sub-blocks are connected to Module 3 as a skip connection.

The skip connection in the initial sub-blocks is combined in module 4, which is used for that purpose.

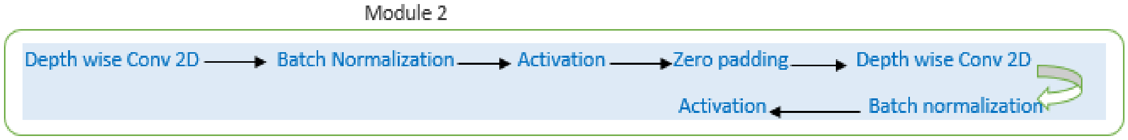
Module 5: Using a skip connection, each sub-block is connected to its preceding sub-block before being concatenated.

Efficient Net (BNs) models' architecture is mentioned below in the flow diagram in figure.

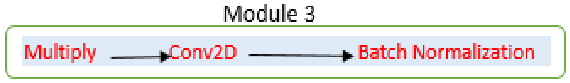


Module 1

Module 2



Module 3



Module 4

Module 5

Figure 3. 9 The architecture of the Efficient Net Model

They compared the Efficient Net's performance with other effective learning models when arranged on the data set of Image-net. This one has exhibited the existing version of Efficient Net B7 that has the maximum accuracy among the minimum number of parameters of models. Efficient Net (BNs) model parameters and flops are mentioned which have been used to train our datasets in Table.

Model	Parameters	Flops
Efficient Net-B0	5.3 M	0.39 B
Efficient Net-B1	7.8 M	0.70 B
Efficient Net-B2	9.2 M	1.0 B
Efficient Net-B3	12 M	1.8 B
Efficient Net-B4	19 M	4.2 B
Efficient Net-B5	30 M	9.9 B
Efficient Net-B6	43 M	19 B

Table 3. 3 Parameters and Flops of Efficient net BNs

3.7 Training:

Efficient Net B (0–6) was used to train our datasets through the use of hyper-parameters. Adam's optimizers were used to implement training for the displayed model, and the learning rate was set to 0.0001. We divided the EYE-PACS data into three groups for training, testing, and validation. 30194 fundus images make up the training set, while 2457 images were included in the test and validation datasets. In data of DeepDRiD 1408 retinal fundus images in training data, in contrast, the test and validation dataset has 96 images. For EYEPACS and DeepDRiD, the weights of the network were randomly initialized with batch sizes ranging from 30 to 12. Then, for the EYE-PACS dataset, we trained a network for 20 epochs, and for the DeepDRiD dataset, for 100 epochs. An objective function was the categorical cross-entropy. These hyper-parameters are given below in Table.

Serial No.	Hyper-parameters	Values
1	Learning Rate (LR)	0.0001
2	Epochs(EYE-PACS) Epochs(DeepDRiD)	20 100
3	Optimizer	Adam
4	Loss Function	Categorical Cross-Entropy

Figure 3. 4 Hyper-parameters in training

These hyper-parameters are very useful which play vital role in training desire models on given databases.

3.8 The Performance Metrics:

The Efficient Net BNs models' AUC, f1 score, accuracy, and recall values have been discovered.

F1Score:

It is helpful to calculate the harmonic average of recall and precision as:

$$\text{F1Score} = \frac{2 \times precision \times recall}{precision + recall}$$

Precision:

Specifically, the ratio of true positives to components is stated as being acceptable for the positive class (i.e., the sum of true positives (TP) and false positives (FP)). To show the precision, the Positive Predictive Value (PPV) is used. An equation for precision is:

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

Recall:

It can be expressed as the proportion of TN parts to all parts belonging to the negative class (such as the total of FP and TN). The mathematical representation of the appearance is:

$$\text{Recall} = \frac{TN}{TN+FP}$$

AUC:

It is the area under the curve and has been used to execute a fixed integral among the two points. The evaluating equation is:

$$\text{Area under the Curve} = \frac{1}{2}\left(\frac{\text{True positive}}{\text{True positive+False negative}} + \frac{True\ negative}{True\ negative+False\ positive}\right)$$

CHAPTER 4: RESULTS

4.1 The System Configurations:

Efficient Net BNs models have been implemented in MONAI open-source architecture. The output channels of models are analogous to five classes DR_0, DR_1, DR_2, DR_3, DR_4. We used Cross Entropy Loss as a loss function. A system with some parameters was utilized for the methodology.

- Python 3.8.8
- Ubuntu Version 20.04.4 LTS
- NVIDIA Tesla T4 GPU with 16 GB memory
- RAM 32 GB memory
- CUDA version 11.4
- Deep learning architecture Pytorch 1.9.0 and MONAI 0.8

4.2 Results Evaluation:

F1 scores were calculated by using six Efficient Net BNs classification models. We have followed the (Maida et al., 2022) studies and deployed Efficient Net B (0, 1, 2, 3, 4, 5, 6) on EYE-PACS and DeepDRiD datasets. We got evaluating scores from all models of Efficient Net Bns except Efficient Net B7. The Efficient Net models could distinguish all classes. In addition, the Efficient Net BNs have identified all the classes with great possibility; later the F1 score is elevated for Efficient Net BNs models in contrast to the VGG and Res Net models. The idea behind an efficient network is that larger input images require more layers in order to enhance the receptive field and more channels in order to capture more minute patterns on the larger image. An order-of-magnitude smaller and faster family of image classification models called Efficient Nets achieves state-of-the-art accuracy. We already had the top model on the validation test after training and validation. To determine whether the model is reliable and not over-fitted, we assessed it using a test dataset. These forecasts had been be used to create a classification report. The best model metric in DeepDRiD dataset had approximately AUC score on validation set. And the best model metric in DeepDRiD dataset had approximately 0.98 Val AUC score. The best model metric in EYE-PACS dataset had approximately 0.90 Val AUC score. We got AUC scores on validation data set after the training had been completed. After that we evaluated test data F1 scores in form of classification reports. Two classification reports on EYE-PACS and DeepDRiD test sets are mentioned in the below Figures.

	precision	recall	f1-score	support
DR-0	0.90	0.97	0.93	1783
DR-1	0.46	0.29	0.36	199
DR-2	0.72	0.58	0.64	360
DR-3	0.46	0.65	0.54	63
DR-4	0.93	0.50	0.65	52
accuracy			0.84	2457
macro avg	0.69	0.60	0.62	2457
weighted avg	0.82	0.84	0.83	2457

Figure 4. 1 Classification report on deployment of Efficient net b6 on EYE-PACS Dataset

	precision	recall	f1-score	support
DR-0	0.93	0.95	0.94	39
DR-1	1.00	1.00	1.00	7
DR-2	0.79	0.79	0.79	19
DR-3	0.92	0.88	0.90	26
DR-4	0.40	0.40	0.40	5
accuracy			0.88	96
macro avg	0.81	0.80	0.81	96
weighted avg	0.87	0.88	0.87	96

Figure 4. 2 Classification report on deployment Efficient net b5 on DeepDRiD

In the above table metric scores of previous work utilized a Kaggle EYE-PACS dataset and deployed the model of Efficient Net b3, which was capable to identify entire stages of DR with an F1 score of 0.84 (Maida et al., 2022). And our proposed work used DeepDRiD and EYE-PACS datasets and established the model of Efficient Net b5, which is accomplished to spot all diabetic retinopathy stages along F1 scores of 0.88 & 0.84 which are much higher than previous work on these models and similar dataset. However, we deployed these models on DeepDRiD and evaluated F1-score first time. The projected model displayed greater accuracy for identifying and sorting diabetic retinopathy on DeepDRiD and Kaggle EYE-PACS datasets. In Figure 4.3 and 4.4 epoch average and validation AUC graphs of DeepDRiD and EYE-PACS are drawn.

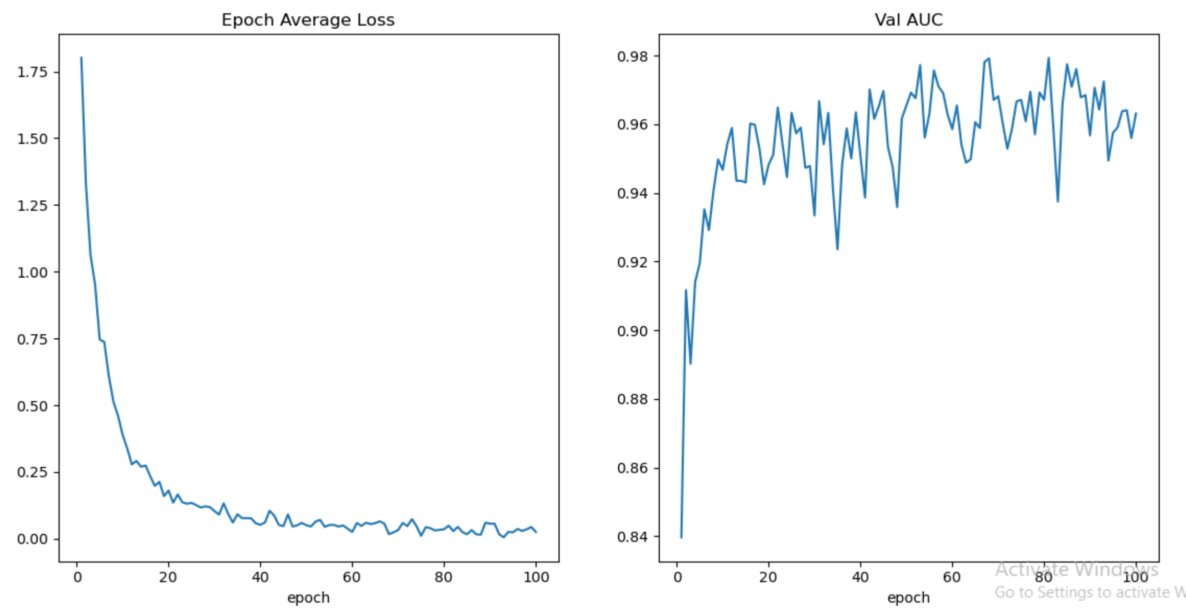


Figure 4. 3 Plot the Epoch Average loss and Val AUC of the DeepDRiD dataset

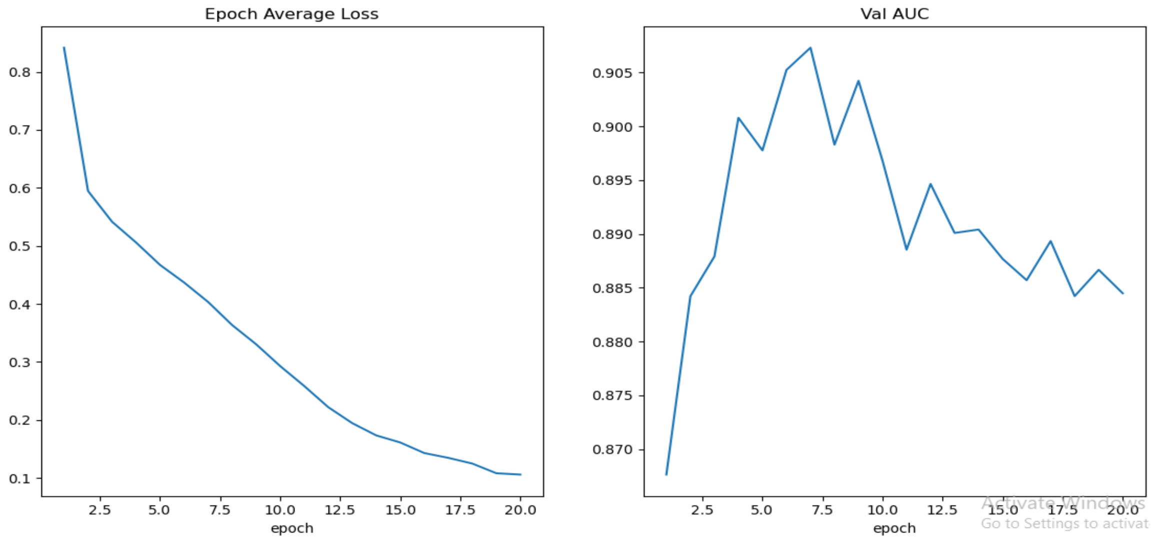


Figure 4. 4 Plot the Epoch Average loss and Val AUC of the EYE-PACS dataset.

These graph displayed AUC score on validation set of both datasets (EYE-PACS and DeepDRiD. We ran a training session that included step and epoch loops, with validation performed after each epoch. Then kept the model weights in a file if the validation accuracy was the best. Applying coefficients (estimates) derived from the training sample to the validation sample results in the calculation of the AUC. We referred to this procedure as scoring. And that is said to be validation AUC. Additionally, we may calibrate probability cutoffs and further improve our models utilizing probabilities and AUC. As a result, the AUC metric is what we advise using as it makes use of prediction probabilities. A given model is evaluated using the validation set, although this is done frequently. This information is used by deep learning developers to adjust the model hyper parameters. As a result, even if the model occasionally encounters this data, it never "Learns" from it. We update higher level hyper parameters using the validation set findings. In this way, a model is indirectly impacted by the validation set. And after that we would get evaluating AUC score on validation set. After that we would get evaluation score on test set. In below table we deployed seven Efficient Net bns models and we acquired F1 score on test databases. Efficient Net B0 is less number of parameters then all other six models. Highest number of parameters &flops used in Efficient Net B6. We deployed these models in our EYE-PACS and DeepDRiD datasets and compare our F1 scores with recent studies deployed on EYE-PACS dataset (Maida et al., 2022). There is table of evaluating score of metrics for all the Efficient Net BNs models given below:

Efficient Net Bns Models	**Precision**	**Recall**	**F1-Score on test data**
Our proposed B0 (DEEPDRiD)	0.85	0.83	0.83
PREVIOUS B0(Maida et al., 2022)	0.69	0.77	0.70
Our proposed B0 (EYE-PACS)	0.80	0.82	0.82
Our proposed B1 (DEEPDRiD)	0.87	0.84	0.84
PREVIOUS B1(Maida et al., 2022)	0.69	0.78	0.72
Our proposed B1 (EYE-PACS)	0.81	0.83	0.83
Our proposedB2 (DEEPDRiD)	0.84	0.84	0.84
PREVIOUS B2(Maida et al., 2022)	0.67	0.77	0.71
Our proposed B2(EYE-PACS)	0.80	0.84	0.84
Our proposed B3 (EYE-PACS)	0.83	0.81	0.81
PREVIOUS B3(Maida et al., 2022)	**0.83**	**0.85**	**0.84**
Our proposed B3 (DEEPDRiD)	0.81	0.84	0.84
Our proposed B4 (DEEPDRiD)	0.85	0.83	0.83
PREVIOUS B4(Maida et al., 2022)	0.69	0.77	0.70
Our proposed B4 (EYE-PACS)	0.81	0.83	0.83
Our proposed B5 (DEEPDRiD)	**0.87**	**0.88**	**0.88**
PREVIOUS B5(Maida et al., 2022)	0.52	0.72	0.72
Our proposed B5 (EYE-PACS)	**0.82**	**0.84**	**0.84**
Our proposed B6 (DEEPDRiD)	0.86	0.86	0.86
PREVIOUS B6(Maida et al., 2022)	0.70	0.77	0.72
Our proposed B6 (EYE-PACS)	0.82	0.84	0.84

Table 4.1 Evaluating metric scores for all the Efficient Net BNs

The F1 scores are evaluated on test datasets and in above table we mentioned F1 scores of seven various Efficient Net bns models. We started to observe result scores with least parameters and flops (Efficient Net B0) to highest parameters and flops containing model (Efficient Net B6). Then compared our two datasets results with recent research studies on EYE-PACS Kaggle dataset (Maida et al., 2022). The highlighted scores in the tables showed recent studies (Maida et al., 2022) and our highest scores.

CHAPTER 5: DISCUSSION

Scientists are noticing broad investigations to describe DR classes. There is a significant aim for selecting this disease in the research that this disease is frequent in China, the USA, and India, and has in recent times taken place to develop generally in our country. In future research, we will work on planning an effective DR classification system in which numerous models can be cohesive with a web-based interface for usage in clinical purposes. The basic drive of using these classification models is to grade all stages of diabetic retinopathy. Previously other CNN classification models have not classified all classes. An Efficient Net BNs model is the most effective CNN multi-classification of Diabetic Retinopathy, rather than VGGs and Resents. The focal objective of our work was to deploy such an effectual model which classifies all stages of DR. Applying a few simple preprocessing techniques, dataset resizing with high-resolution images, and a Gaussian Smooth filter. We implemented Efficient Net models to enhance performance and categories at every stage. While we were able to achieve 0.79 to 0.84 by applying Efficient Net (1-6) BN models, previous work using Efficient Net BN models deployed on the EYE-PACS dataset only acquired 0.84 F1-score by Efficient Net B3. Our models raised the EYE-PACS Kaggle dataset's F1 score, which was employed in earlier research (Maida et al., 2022) but the DeepDRiD 2020 dataset, which we used, had a higher F1 score than the Kaggle dataset. In the EYE-PACS dataset, all of our classes have scores; however, in DeepDRiD, the majority of our classes have scores above 78%, and one of our illness classes has a score of 100%. A few researchers had also previously worked with limited data on diabetic retinopathy. We were unaware that employing Efficient Net models with DeepDRiD little data did not evaluate F1 scores in the literature. As a result, we observed the little DeepDRiD dataset while simultaneously using the older Kaggle dataset in our investigations. We even achieved the top score using a different, smaller DeepDRiD dataset. With a higher F1 score of 0.88 & 0.84, the Efficient Net b5 and b6 models on the DeepDRiD and EYE-PACS datasets detected all the types of DR. On the DeepDRiD dataset, however, we attained the greatest F1 score of 0.88. Our suggested research offers scores for smaller datasets like DeepDRiD in addition to S-O-T-A outcomes for huge datasets like EYE-PACS. One disadvantage of datasets larger than 6GBs is that these CNN models cannot be trained on the available GPU. Due to the extensive parameters compared to other Efficient-Net bns that were used in our work, we were also unable to train EYE-PACS data using Efficient-Net B7.In later research, we can use Efficient-Net b7 for the same datasets. The algorithms have a number of shortcomings that prevent them from classifying with high image resolution in datasets on Google-Colab, including extraordinarily high computational costs, the lack of use of complex preprocessing and data augmentation techniques, and the failure to add additional features to the models. We may test the performance of the models using ensemble models, k-fold cross-validation, future changes in model topologies, and other state-of-the-art structural designs like CoAtNet. The main goal of the proposed effort is to create a computer-aided diagnosis tool that can identify and categorizes diabetic retinopathy in its early stages. There weren't many works where CNN was employed and good results were obtained, according to a thorough review of the existing works. The suggested method still has room for development. To entirely remove the noise from the dataset, the pre-processing module might be modified.

CHAPTER 6: CONCLUSIONS

A very tiny investigation into separating all diabetic retinopathy groups with a higher F1 score has just been completed. Gradually separated DR screening techniques will make the screening procedure highly efficient, affordable, and available. We used Efficient Net BN models in our paper. It has been noted that grade 0 of DR occurs more frequently in other CNN models. In earlier research, we found that applying ResNet and VGG models, which were scaled only by their depth, suggested that they were unable to obtain the parameters of the images that resembled classes. Previously used Efficient Net models consistently scaled the depth, width, and resolution using the compound scaling technique More than one class of DR can be distinguished by the primary factor of Efficient Net BN models (Tan et al., 2019). Future improvements will be needed, and these can be made by applying advanced preprocessing and data augmentation techniques, using images with the highest resolution possible, applying an ensemble of multiple CNN classification models, or using a model similar to this one but with additional features to achieve the best possible outcome.

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