A Deep Learning Framework for Detection and Classification of Diabetic Retinopathy in Fundus Images Using Residual Neural Networks

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***Abstract* - Diabetic retinopathy is a damage to the blood vessels in the eye caused by diabetes. Failure to diagnose it in time can result in permanent vision impairment or blindness. Regular disease screening has traditionally been a time-consuming and costly endeavour. Utilising computer technology to detect these diseases automatically would be an effective method. In recent years, we have seen a rise in interest in the use of Convolutional Neural Networks (CNNs), a subcategory of deep learning systems, as a potential method for the evaluation of medical images. To classify fundus images into different severity levels using the ResNet-50-CNN architecture is the primary focus of this work. The effectiveness of the algorithm can be evaluated using the Kaggle blindness dataset APTOS 2019. The paper will focus on both binary and multiclass classifications of DR. On the APTOS dataset, the accuracy for training and validating two-class models is 96% and 95%, respectively. The accuracy of training and validation for classification of multiple classes in the extended APTOS dataset is 80% and 77%, respectively .**

Keywords— Diabetic Retinopathy, Convolutional Neural Network(CNN), Deep learning, Fundus images, ResNet-50

I. INTRODUCTION

In recent years, there has been a dramatic rise in the worldwide prevalence of diabetes, also known as Diabetes Mellitus (DM). The number of people with diabetes is expected to rise to 439 million by the year 2030. [1]. These forecasts come from the World Health Organization. Diabetic retinopathy (DR) is a primary cause of blindness globally and one of the most serious outcomes of diabetes mellitus. Diabetic retinopathy is a serious eye disorder that is brought on by high blood sugar levels. These levels cause damage to the blood vessels that are located behind the retina, which can eventually lead to bleeding. In later stages, the disease causes the retina to produce tiny new blood vessels, which rupture can lead to visual blockage and irreversible vision loss. Each stage is characterized by a unique set of symptoms[2]. In addition, current methods of diagnosing DR are ineffective because they are extremely time consuming; As a result, the medication may be administered incorrectly. When diagnosing DR, ophthalmologists often use an approach known as conventional fundus image analysis. If a person does not receive the best care, the disease can lead to permanent vision damage or even blindness. Therefore, it would be very helpful if the disease could be detected earlier in a more efficient and economical manner. Micro aneurysms (MA) can be detected and analysed with this technique. MAs are the most important indicator of DR. Methods using Computer-aided Automated Diagnosis (CAD) can identify Diabetic Retinopathy in a small time and provide high accuracy[3].

Diabetic Retinopathy can be diagnosed based on the size, shape, color, and texture of the symptoms, such as hard and soft exudates, microaneurysms, cottonwool spots, retinal hemorrhages and neovascularization. Diabetic retinopathy can be divided into two distinct phases: the proliferative form (Proliferative Diabetic Retinopathy) and the non-proliferative form (Non Proliferative Diabetic Retinopathy) [4].

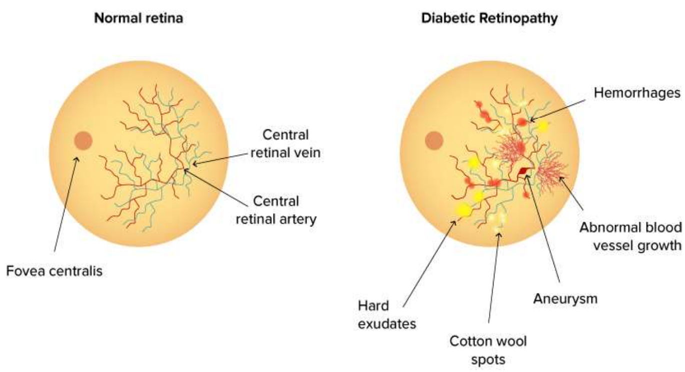

Fig .1. Diabetic Retinopathy vs. Normal Retina[1]

Additionally, the NPDR can be subdivided into three phases, which are referred to as the Mild, Moderate, and Severe levels. High blood sugar levels are responsible for NPDR because they start to damage tiny capillaries in the retina that carry blood. Because of this, the blood vessels in the eye become more dilated and begin to leak fluid; as a result, the retina does not receive the proper amount of oxygen and nutrients. [4]. As a consequence of this, the body generates vascular endothelial growth factor, also known as VEGF, in order to provide nutrients and oxygen to the retina of the eye. However, these new cells are delicate and have a high risk of being injured, which may lead to an increase in swelling and leakage. Proliferative diabetic retinopathy, also known as PDR, is a more advanced form of diabetic retinopathy that, if untreated, can result in significant and irreversible loss of vision. [6].

Diagnosing a DR can be done either manually by ophthalmologists or automatically by a computer system. When diabetic retinopathy occurs in its early stages, its early symptoms are so minor that ophthalmologists may even ignore them. Artificial intelligence is gaining importance in the detection of serious conditions like diabetic retinopathy (DR). Compared to the manual method, the automated diabetic retinopathy detection method is far superior in terms of authenticity, reliability, speed, efficiency and ease of use. The primary objective of this study is to analyse current deep learning patterns and demonstrate ResNet's effectiveness in identifying DR at its various stages using a successfully pre-trained model.

Table 1. Different types of lesions correspond to different stages of DR.

Stages of DR	Features
No DR	No lesions present
Mild NPDR	Presence of Microaneurysms only.
Moderate NPDR	More common than microaneurysms but less harmful than NPDR
Severe NPDR	• Presence of venous beading in two quadrants. • Presence of Intra -retinal Haemorrhages in four quadrants
PDR	Presence of Neovascularization, Vitreous/preretinal haemorrhage

Deep learning is the most famous and effective way to find DR in ophthalmology. When it comes to machine learning (ML), deep learning is a subfield that utilises neural network-based techniques. CNNs are an important part of DL methods, mainly used to analyze data from images. Here, we employ ResNet -50 to develop an automated detection system for DR lesions, and we show that it can identify lesions at both stages 2 and 5 [3].

This research study applies the ResNet 50 model to retinal images to evaluate the model's effectiveness for the classification of DR in various stages.

• Binary classification(2 stage) used to differentiate between Normal and Diabetic Retinopathy images.

• Multiclass classification(5 stage) is about identifying Diabetic Retinopathy as well as different degrees of Diabetic Retinopathy affecting the retinal image.

The remaining sections are organized as follows. Brief analysis of deep learning-based related work on DR stages are explained in section 2. Datasets, Image pre-processing, feature extraction and classification with ResNet-50 are all discussed in Section 3 of the paper, along with the proposed approach and how it was developed. Experimental results, discussion and analysis are presented in Section 4. Section 5 summarises research findings and future study recommendations.

II. RELATED WORKS

CNN is widely used to classify and locate retinal fundus images. DR detection is done using deep learning and can be divided into a two stage DR classification and five stage DR classification.

Masood et al. [7] used transfer learning on CNN, which was based on Inception-V3 and pretrained on ImageNet. Kaggle EyePacs datasets, which include five stages, were used to obtain an accuracy of 48.2%.The Convolutional Neural Network model developed by Gosh et al. [8] achieved 95% accuracy for two categories of diabetic retinopathy problems and 85% accuracy for five problem categories after being applied to a dataset of 30,000 images.

Yang et al. [9] suggested using a deep CNN with two stages to look at diabetic retinopathy. Their method showed the type of lesion based on its position in the fundus image and the severity of each lesion in each image. The performance of their suggested algorithm got even better when they added an unbalanced weight map. They re-annotated the grades for 23,595 images and labelled 12,206 lesion locations in the dataset that was provided by EyePACS.The suggested algorithm was 95.95% accurate.

Garcia et al. [10] provided a way to split the Kaggle Eyepacs dataset into two parts . After that, the datasets would be trained using the CNN model separately for each eye. They achieved a level of accuracy that was 63.6% for left eye and 66.4% for right eye correspondingly.The phases in the IDRiD dataset were classified using Resnet50 with attention modules, which resulted in a cumulative accuracy of 65.1% according to Li et al. [11].

Weighted pathways convolutional neural network (WP-CNN) was created by Liu et al. [12] for the goal of categorising Diabetic Retinopathy images in a private dataset.They estimated that their accuracy was 94.23%.The DR phases in the Kaggle APTOS 2019 dataset were classified 77% correctly by Dekhil et al.[13] using VGG 16.

The classification of the DR into five phases was performed by Xiaoliang Wang et al.[14] using different deep neural networks. They trained 166 fundus images on Alex NET, VGG16, and Inception Net architectures using the EYEPACS dataset, with the Inception Net architecture providing the best accuracy of the three.Pires et al. [15] proposed employing a custom-built Convolutional Neural Network (CNN) to differentiate between Dr and No- DR images.Achieving an AUC of 98.2% on the Messidor-2 was accomplished with CNNs trained with the help of the Kaggle.

Jiang et al. [16] created a new dataset with the intention of classifying DR images as either DR or No-DR using three pretrained CNNs. These CNNs were Inception-Resnet-V2, Inception V3, and Resnet 152.Using the Adaboost technique, these CNNs were integrated into a single network.They were able to acquire an AUC of 0.946.

Harangi et al. [17] categorized the DR levels by combining handcrafted functions and Alex net. For training purposes, they used the Kaggle dataset, and for testing purposes, they utilised the IDRiD dataset. The approach was successful in achieving an ACC of 90.07 %.

Patients who have diabetic retinopathy can be diagnosed with the help of digital fundus images, according to a proposal that was made by Pratt et al.[18] using a Convolutional Neural Network (CNN) model. They used an openly available Kaggle dataset consisting of 80,000 images. They were successful in attaining a rate of accuracy of 75% over the entire set of 5,000 validation images.

Table 2 Summary of Related works

Author	Data sets used	***methodology***	***Results***
Masood et al[7]	Kaggle EyePAcs	Inception-V3	5 class Accuracy-48.2%
Gosh et al[8]	Kaggle EyePacs	CNN with denoising technique	2 class-95% 5 class-85%
Yang et al[9]	Kaggle EyePacs	Two stage deep CNN	95.95%
Garcia et al[10]	Kaggle EyePacs	CNN	63.6% for left eye,66.4% for right eye
Li et.al [11]	IRiD	Resnet 50	5 class-65.1%
Liu et al [12]	Private dataset,STARE	WP-CNN	2 class-94.23%
Dekhil et.al [13]	APTOS 2019	VGG-16	5 class-Accuracy76%
Xiaoliang Wang et al[14]	Kaggle Eyepacs	Alexnet Vgg-16 Inception v3	37.43%,50.03%,63.23%
Pires et.al[15]	Messido-2,DR 2	Custom CNN	AUC-98.2%
Jiang et.al[16]	Private Dataset	Inception,Resnet-V2,Inception V3 Resnet 152	AUC-0.946
Harangi et. al[17].	IDRiD	Alexnet	90.07%Accuracy
Pratt et. al[18]	Kaggle eyepacs	CNN	70%Accuracy

III.PROPOSED METHODOLOGY

The DR diagnostic model developed in this study basically consists of the three processes listed below: input data pre-processing, a feature extraction network, and classifiers. According to the figure 5, the proposed structure consists of three stages of the pipeline : a pre-processing stage that performs intensity normalization and horizontal and vertical flipping expansion, a feature extraction phase using a Res-Net 50 model,a prediction phase; and finally an output stage.

Dataset

The APTOS 2019 dataset was obtained from the Kaggle website [21] and used as the basis for the classification experiments performed in this work. The Aravind Eye Hospital in India was responsible for compiling this data collection, which includes 3662 high-resolution photos with each specimen attached and a diagnosis made by highly competent medical professionals. Depending on the diagnosis, these images were assigned one of five different severity levels for diabetic retinopathy. There are 1805 normal images in the grade 0 category, indicating the absence of diabetic retinopathy; 370 images in the grade 1 category, indicating the presence of mild nonproliferative diabetic retinopathy; 999 images in the grade 2 category, indicating moderate non-proliferation; and 193 images in the grade 3 category, indicating severe non-proliferative diabetes. We separated the dataset for training, testing, and validation purposes to achieve a more even distribution of the data.

A total of 2,929 color fundus photos were considered for training purposes and 733 color fundus images were examined for validation purposes. Figure 2 demonstrates that the dataset that was provided by Kaggle had a class allocation that was quite unevenly distributed .

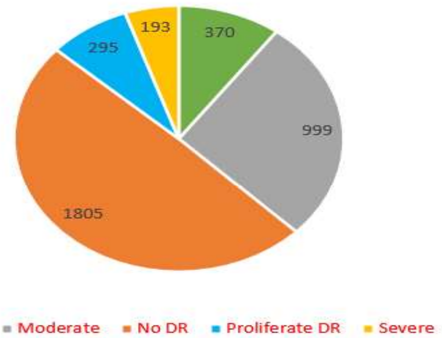

Fig.2.Number of Images in Each Grades

B. Preprocessing Stage

The dataset was then subjected to a series of image pre-processing processes in order to improve the overall picture quality. The entire dataset was then split into a training set and a test set. On the images that comprised the training set, data enhancement techniques including rescaling, horizontal flip, vertical flip, rotation, and shifting width and height wise were employed.

C . Feature extraction and classification

Figure 5 is a short description of the proposed approach that we have designed for binary and multiclass classification.Here we used Resnet-50 deep learning network for feature extraction and classification.

RESNET-50

Resnet -50 is a very common neural network architecture these days. It is a Convolutional Neural Network with more than 25 million parameters and 50 layers. [25]. We have adopted pre-trained weights in the imagenet, so that the model has already learned various basic functions. There are 48 convolutional layers in Resnet-50, along with a maximum pooling layer and an average pooling layer. The interconnection between layers retained in this architecture helps mitigate the problem of accuracy saturation. The added shortcut connection is used to perform identity mappings. The basic idea of this skip connection is shown in Figure 3. Such skip connections add the outputs of the previous blocks to the following ones as expressed by the following equation:

$$Z = F(x) + x \tag{1}$$

Where x is input, Z is output, and F is the residual function.

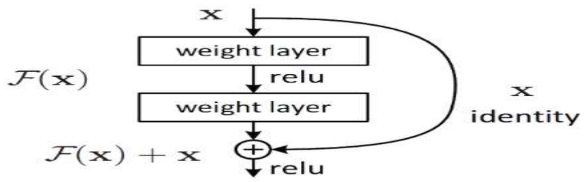

Fig.3.Skip connection used in ResNet architecture.

Each of the five stages of the ResNet 50 model is made up of a convolution block and an identity block. Convolution, an identity block where input and output are equal, and a fully connected layer are all components of this set. The architecture of ResNet50 is shown in Figure 4 below.

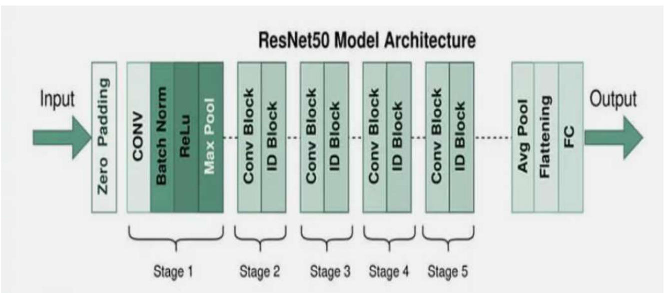

Fig.4. ResNet-50 Architecture[25]

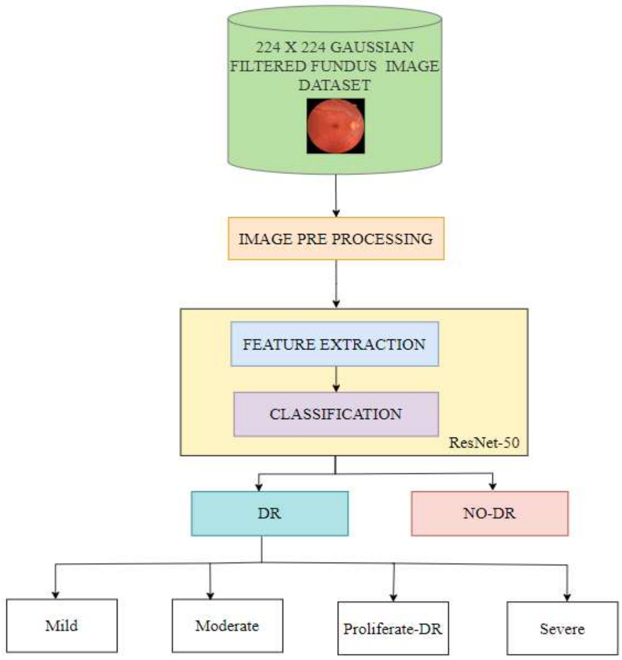

Fig.5. Block schematic for ResNet-50-based DR categorization

D. *Performance measures*

When evaluating the overall effectiveness of the study, metrics such as accuracy, precision, sensitivity, and specificity, as well as the F1 score, are taken into consideration. The degree to which each model is accurate is determined by calculating the ratio of the total number of labels that have been correctly identified to the total number of pictures that fall into each category.

$$\text{Sensitivity or Recall} = TrPo / (TrPo+FaNe) \tag{1}$$

$$\text{Precision} = TrPo/(TrPo+FaPo) \tag{2}$$

$$\text{Specificity} = TrNe/(TrNe+FaPo) \tag{3}$$

$$\text{F1 Score} = 2*(\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision}) \tag{4}$$

$$\text{Accuracy} = (TrPo+TrNe) / (TrPo+FaPo+FaNe+TrNe) \tag{5}$$

where TrPo stands for True Positive, TrNe stands for True Negative, FaNe stands for False Negative, and FaPo stands for False Positive.

Cohen's kappa : Basically, it tells you how much better the classifier's performance is than the performance of a classifier that just randomly guesses based on the frequency of each class.

IV. RESULTS AND DISCUSSIONS

The system uses an NVIDIA graphics processing unit with a memory of 8 GB. For the training and evaluation of the proposed work, the Keras API running on the Tensor flow in Python was used.

A . Binary classification result

50 epochs were employed during model training, and the Adam optimizer was used throughout. The categorical cross entropy was used as the loss function. In order to categorise Diabetic Retinopathy as Normal and DR, the input picture is scaled down to 224 x 224 pixels and then used as input for ResNet 50, a deep neural network. After compiling the data, an analysis is performed by plotting the loss function and accuracy versus epochs. From Figure 7 we can see that the loss is minimal. The model's test accuracy is 95%, calculated from the confusion matrix in Figure 8. All performance indicators, including precision, recall, and F1 score, are at 95%,and the binary classifier's Cohen Kappa's score is 0.910. The classification results for each level are described in Table 3.

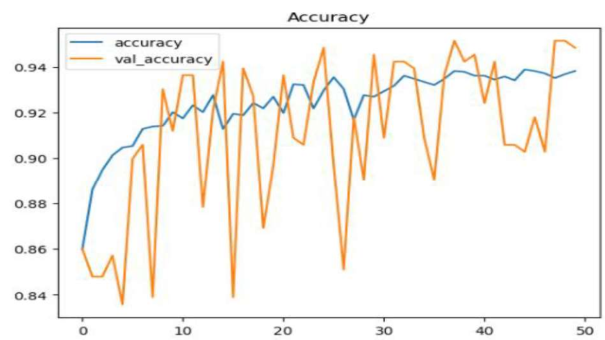

Fig.6. Accuracy curve of Binary class

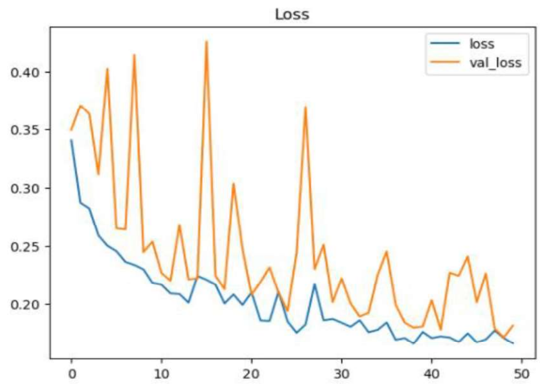

Fig.7. Loss curve of Binary class

Table 3 Class-wise results of Binary classifier

Model	Ac-cu-racy	Class	Preci-sion	Re-call/sen sitivity	F1-Score
ResNet 50(Bi-nary class)	95 %	DR	0.95	0.95	0.95
		N0-DR	0.95	0.95	0.95
		Macro-Average	0.95	0.95	0.95
		Weighted -Average	0.95	0.95	0.95

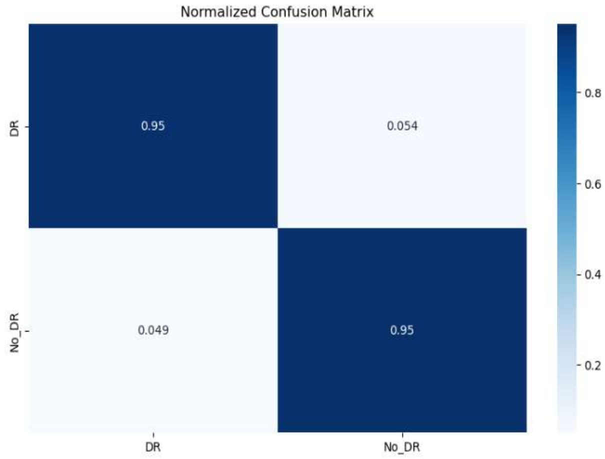

Fig.8. Confusion matrix of Binary class

B. Multi Stage classification result

The image size is changed to 224 x 224 and the results are analysed for a total of 50 epochs in order to identify DR images belonging to each of the five categories. Figure 9,10shows the accuracy and loss curve of multi stage classification .Accuracy of the model is calculated from the Confusion matrix shown in Fig 11 and class wise performance measures for each stages are described in Table 4.

The accuracy, recall, and F1 score provided by the model are 74%, 77%, and 73% respectively. Moreover, the binary classifier's Cohen kappa score is 0.765.

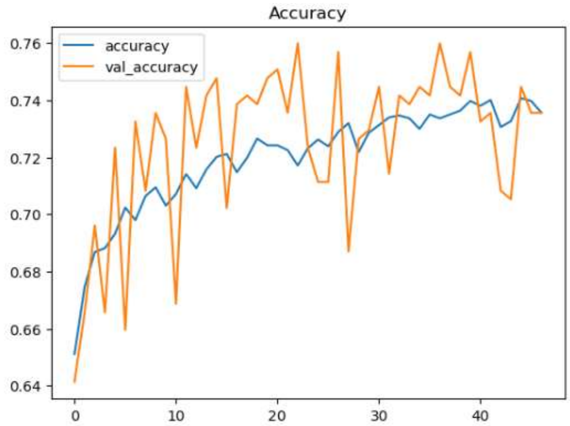

Fig.9. Accuracy curve of Multi classifier

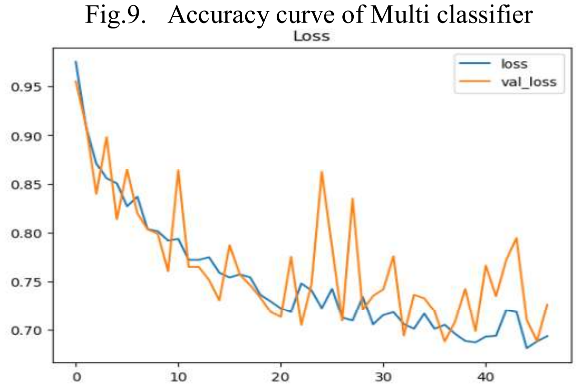

Fig.10. Loss curve of Multi stage classifier

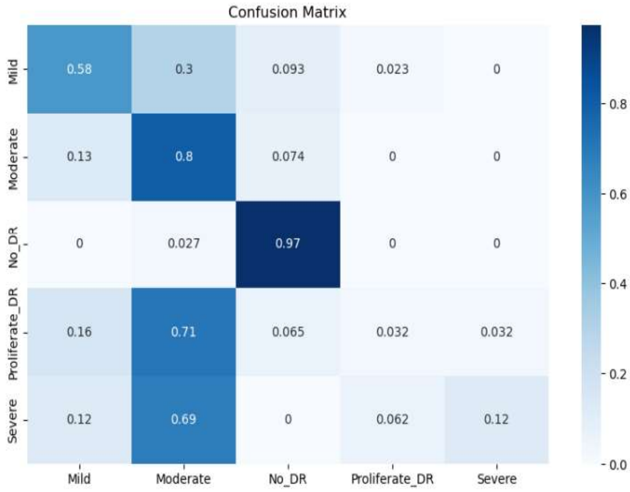

Fig.11. Confusion matrix of Multistage classifier

Table 4 Class-wise results of Multistage classifier

Model	Accu-racy	Class	Pre-ci-sion	Re-call	F1-Score
ResNet 50(Five class)	77%	Mild	0.57	0.58	0.57
		Moderate	0.60	0.80	0.68
		No-DR	0.93	0.97	0.95
		Prolifer-ate-DR	0.33	0.03	0.06
		Severe	0.67	0.12	0.21
		Macro Average	0.62	0.50	0.50
		Weighted Average	0.74	0.77	0.73

Table 5 Comparative analysis of the proposed model and existing models

Author	Classes	Methodology	Accuracy
Masood et. al[7]	5	pretrained Inception-V3	48.20%
Li et.al [11]	5	Resnet 50	65.10%
Liu et al [12]	2	WP-CNN	94.23%
Dekhil et.al [13]	5	VGG-16	76%
Xiaoliang Wang et al[14]	5	Alexnet	37.43%
		VGG-16	50.03%
		Inception V3	63.23%
Pratt et al[18].	5	CNN	70%
Proposed method	**2**	**ResNet 50**	**95%**
	5		**77%**

V. CONCLUSION

Both the number of diabetes cases and their most common consequence, diabetic retinopathy (DR), are increasing worldwide. Therefore, early diagnosis and treatment of DR is essential if one wants to reduce the risk of blindness. The manual diagnostic method of DR is not nearly as effective as its automated counterpart. Therefore, it is more time, labor and cost efficient to automate the DR diagnostic process through the use of computerized solutions. Through the use of deep learning, positive results can be achieved in the field of disease diagnostics. This study uses the ResNet model trained on the APTOS dataset to perform binary and multiclass classification with a deep convolutional neural network. The results of the experiments lead us to conclude that a deep layer model like ResNet-50 can improve the data set overall.

VI. FUTURE SCOPE

In the future, the current research could be expanded to include the performance of the ResNet model compared to other ResNet models, the ResNet model compared to other deep layer networks, and the results of applying the ResNet model after completing various image preparations analyze processing methods compared with each other. All of these comparisons could be made in the future.

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