Detection and Classification of Diabetic Retinopathy using Pretrained Deep Neural Networks

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***Abstract*— The retina is harmed by diabetic retinopathy (DR), a consequence of diabetes. Up to, 80% of people who have had diabetes for ten or more years are affected by this type of medical issue. Where the need for diabetic retinopathy identification is greatest, there is frequently a shortage of the necessary knowledge and tools. The majority of research in the area of diabetic retinopathy has relied on manual feature extraction or disease identification. So, the goal of this research is to make a deep learning neural network that can identify the disease in all of its forms. The suggested system enables a DR classification that accounts for normal eyes, mild DR, moderate DR, severe DR, and proliferative DR, which may aid ophthalmologists in making a preliminary decision. Our accuracy rates for estimating the degree of diabetic retinopathy from an image were 90% and 92% respectively, using the pre-trained Convolutional Neural Network (CNN) VGG-16 and MobileNet-V2.**

Keywords—Diabetic Retinopathy, Deep learning, VGG-16 MobileNet-V2,Convolutional Neural Networks.

I. INTRODUCTION

Diabetic retinopathy is a severe eye condition which impacts a significant proportion of people with diabetes and is a key contributor to adult blindness worldwide. Diabetic retinopathy can be effectively treated and managed if its presence is identified and classified at an early stage. Manual evaluation of retinal pictures by qualified ophthalmologists is required in the current method for detecting and classifying diabetic retinopathy, But this takes a lot of time and can be different from person to person.[1]

Symptoms of DR may include floaters, blurry vision, and dark or empty spots in the field of vision [3]. Prevention of DR includes controlling blood sugar levels and blood pressure, and having regular eye exams. Early treatment is important to prevent vision loss and other complications associated with DR. The different stages of DR are based on the number of blood vessels and bleeding spots are present and evaluated in fundus of the retina. [2][5]

Various forms of lesions developing on the retina of an image can be used to detect DR. These lesions include soft and hard exudates, haemorrhages, and microaneurysms (MA) (EX) [9][10][11]. Diabetic Retinopathy (DR) lesions can be divided into two categories: red lesions, which include microaneurysms (MA) and haemorrhages (HM), and bright lesions, which include soft exudates (SE) and cotton wool spots (CWS) [1]. Red lesions are typically darker than bright lesions, while bright lesions are usually more defined and easier to detect [3]. The automated detection of these lesions is critical to find and treat DR as soon as possible [6].

Microaneurysms (MA), which look like tiny red circles on the retina and are caused by weak vessel walls, are the first sign of DR. The edges are clean, and it's less than 125 m in size.[7]

Hemorrhages (HM) are larger spots with uneven edges that show up on the retina when they are more than 125 m in size.

Plasma leaks can cause hard exudates, which look like bright yellow spots on the retina. They are in the external layers of the retina, and their edges are sharp.

Soft exudates, also named "cotton wool," are white spots on the retina that constitute when nerve fibres swell.

The different levels of DR severity are as follows and Fig 1 demonstrates how DR undergoes various stages.

Mild Non-ProliferativeDR(NPDR): Microaneurysms start to form in mild non-proliferative DR (NPDR) at this stage. Small patches of balloon-like inflammation can be seen inside the retina's tiny blood capillaries[2][8]

Moderate NPDR: At this point, the blood channels in the retina are blocked.Additionally, there are haemorrhages within the retina. [2]

Severe NPDR - At this stage, More blood vessels are shut off, limiting the retina's various regions of blood flow.Additionally, there is a sharp increase in the amount of retinal haemorrhage. [3]

Proliferative DR- When DR progresses to this latter stage, abnormal blood vessels form at the retina's periphery. Due to the fragility and propensity of these new blood vessels to leak, the eye can experience haemorrhages that can impair vision. Additionally, they will develop into connective tissue that will eventually contract and separate from the retina, leading to blindness. [3]

Automating the way diabetic retinopathy is found and categorised in retinal pictures has shown encouraging results thanks to recent advancements in deep learning. Models trained with deep learning can recognise the signs of diabetic retinopathy by learning complicated features from big datasets.This research introduces a deep learning-based method for diagnosing diabetic retinopathy using retinal images. The method we propose makes use of convolutional neural networks (CNNs) that have been pre-trained on a large dataset of retinal pictures in order to detect and characterise the level of diabetic retinopathy severity.[4] We test our method on a freely accessible dataset and compare the results to those of existing approaches. Overall, deep learning offers a powerful and reliable approach to DR detection and classification.

TABLE I. SEVERITY SCALES OF DR

Stage	Severity	DR signs
I	No-DR	Absence of any lesions
II	Mild DR	Presence of Only Microaneurysms.
III	Moderate DR	More than mild but not as severe DR and presence of cotton wool spots and venous bleeding.
IV	Severe DR	• More than 20 intraretinal Haemorrhages and Microaneurysms in all four quadrants. • Distinct venous beading in two or more quadrants. • There are clear intra-retinal microvascular abnormalities. • No indications of proliferative DR.
V	Proliferative DR	Presence of Neovascularization, Vitreous/pre-retinal HM

Figure 1 provides a clear illustration of the progression of DR through its several phases. It is clear from examining the accompanying figure that both the Normal and Mild phases have a look that is comparable to one another. Because of this, determining whether the condition has reached the Moderate stage might be difficult.

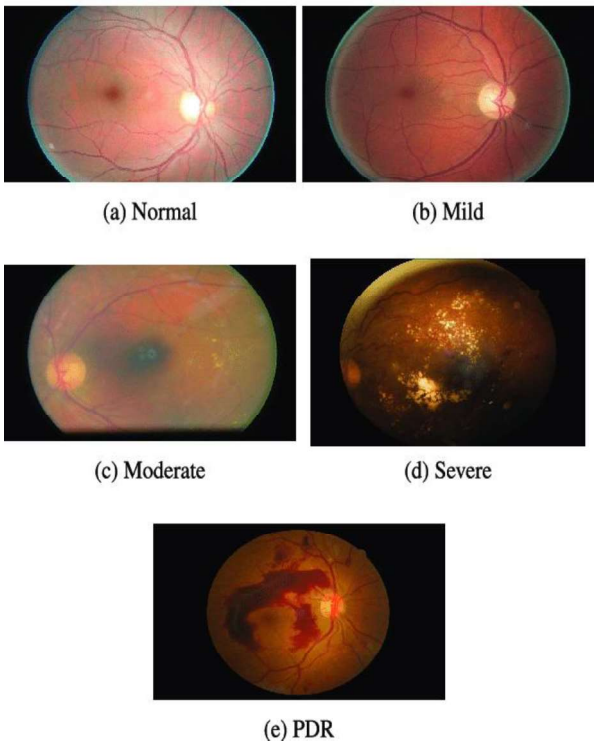

Fig.1: The different stages of DR[5]

II. RELATED WORKS

The identification and classification of diabetic retinopathy have been built into intelligent systems using different types of methodologies.Early detection and grading of DR are essential for preventing vision loss. Traditional methods of diagnosis require manual interpretation of retinal images and it takes a lot of time and is expensive. In this literature review, we will focus on deep Convolutional Neural Networks (CNNs) for lesion detection and grading of DR. Several works that address the primary topic of this study are examined and analysed.

To detect diabetic retinopathy, Gulshan et al. (2016) trained and tested a deep learning algorithm using images of the retinal fundus. The presence of diabetic retinopathy was detected and diagnosed using digital colour fundus images by the authors using convolutional neural networks (CNNs). [12] One dataset had 841 photos from three Indian ophthalmology clinics, and the other contained 110,000 retinal fundus images from Eyepieces. These two datasets were used by the authors to evaluate their CNN model. The CNN model had an area under the receiver operating characteristic curve (AUC) of 0.97, suggesting outstanding performance, and it was reported by the authors to be able to diagnose diabetic retinopathy accurately.

Yang et al. (2017) [13] proposed a two-stage deep convolutional neural network (CNN) approach for diabetic retinopathy detection and grading (DR). They report an 88.27% accuracy for the lesion detection stage and an 83.05% accuracy for the severity grading stage, which outperforms existing methods.

Mansour RF (2017) proposed a computer-aided diagnosis (CAD) system that uses deep learning to find DR in images of the fundus. The author shows that their proposed method has the potential to make DR diagnosis more accurate and faster. For DR detection, the model had an overall accuracy of 97.5%.[14]

Dutta et al. (2018) demonstrated the effectiveness of various deep learning models and their proposed ensemble model for DR image classification. The experimental results show that the deep learning-based models performed well for DR image classification, with the ensemble model outperforming the other models with a 98.1% accuracy. [15]

Lin et al. (2018) suggested a method for converting retinal photos to entropy pictures (DR). The findings from the studies show that the method suggested was able to find DR with a high degree of accuracy, achieving an overall accuracy of 96.72%. The method outperformed ResNet-50 and VGG-19, two cutting-edge deep learning models, in terms of DR detection. [16]

Pao et al. (2020) introduced a bi-channel convolutional neural network (BCNN) in his paper.The experimental findings demonstrated that the suggested BCNN model obtained an overall accuracy of 97.1% for DR detection. Additionally, the model outperformed other cutting-edge deep learning models for DR detection, including VGG16, ResNet50, and InceptionV3.[17]

Kajan et al.(2020) proposed a pretrained deep neural networks as a means of automating the diagnosis of diabetic retinopathy (DR) (DNNs). Overall, VGG-16, ResNet-50, and Inception-v3 all achieved an accuracy of 94.1–95.1% for DR identification with the suggested method. In order to fine-tune the pretrained DNN, retinal pictures from the Kaggle Diabetic Retinopathy Detection (KDD) dataset are used. [18]

Shankar et al.(2020) proposed an automated deep learning based strategy to detect and classify fundus images of diabetic retinopathy (DR). The suggested method employs a synergistic deep learning model that integrates Inception-v3, VGG-19, and DenseNet-121, three distinct CNN architectures. The experimental results demonstrate that the suggested method has a high degree of success in DR detection and classification, with an overall success rate of 96.81 percent. [19]

Mateen et al.(2020) introduced an unique method for detecting exudates in fundus pictures for diabetic retinopathy (DR) using pretrained convolutional neural networks (CNNs). Experimentally, the proposed method exhibited great detection accuracy for exudates, with an overall sensitivity of 91.7% and a specificity of 99.5%. The method beat other cutting-edge deep learning models for exudate identification, such as YOLOv2, Faster R-CNN, and SSD. [20]

Zubair Khan et al.(2021) suggested an architecture based on the merging of two state-of-the-art networks, VGG-16 and NIN (Network in Network), for diagnosing diabetic retinopathy. The potential of deep learning in automated screening and diagnosis of the condition was shown by the suggested method's excellent accuracy in detecting the presence of diabetic retinopathy and grading its severity. [21]

Gothane et al.(2022) proposed a system that uses deep learning to detect Diabetic Retinopathy (DR) in fundus images. The trained model that uses the ResNet 18 architecture can diagnose quickly and respond quickly. Using ResNet architecture, the model was able to correctly classify 82% of the fundus images. [22]

Zhuang et al. (2020) suggested a deep learning strategy for automated categorization of diabetic retinopathy utilising fundus photography. In order to represent the spatial and temporal dependencies of the fundus pictures, the scientists developed a unique network architecture based on a customised version of Efficient net B3, which blends convolutional neural networks (CNNs) with long short-term memory (LSTM) networks. High accuracy of 77.87% was attained in detecting the existence and degree of diabetic retinopathy using this method.[23]

TABLE II: SUMMARY OF RELATED WORKS

Authors	Year	Method	Dataset	Acc
Gulshan et al.[12]	2016	Inception – V3	Kaggle EyePACS	NA
Yang et al.[13]	2017	Deep CNN	MESSIDOR 2 and E-Ophtha	95%
Mansour R. F. et al.[14]	2018	Alexnet	Kaggle Eyepacs	95.26%
Dutta et al.[15]	2018	DCNN: VGGNet	Kaggle EyePACS	82.3%
Lin G.M et al. [16]	2018	CNN	Kaggle Eyepacs	86.10%
Pao SI et al.[17]	2020	Bichannel customized CNN	EyePACS	87.3
S.Kajan et al.[18]	2020	Inception v3 network	Kaggle eyepacs	90.97%
Shankar et al. [19]	2020	Ensemble of Inception-V3,VGG-19,DenseNet-121	Messidor 2	97%
Mateen et al. [20]	2020	Inception-v3, ResNet-50, and VGG-19	DIARETDB1 and E-Ophtha	E-Ophtha-98.43 % DIARETDB1-98.41%
Zubair Khan et al. [21]	2021	VGG-NiN	Kaggle EyePACS	85%
Gothane et al.[22]	2022	Resnet 18	Kaggle fundus images	82%
Zhuang et al.[23]	2020	Modified Efficientnet-B3	EyePACS	77.87%

III. METHODOLOGY AND MATERIALS

A. Data Sets APTOS 2019

For the purpose of detecting diabetic retinopathy, we used data gathered by the Asia-Pacific Tele Ophthalmology Society (APTOS) in 2019 and is available on the Kaggle platform [10]. Gaussian filtered retina fundus images are used to find diabetic retinopathy. As a result of this resizing, the photos are a uniform 224x224 pixels in size, making them compatible with a wide variety of existing deep learning models.

In this dataset, 3662 retinal pictures are included. The fundus photography technique was used to capture these photographs. The fundus photography method is utilised to identify any eye abnormalities that may be present. For the training and testing of our model, we used the dataset of these photos. Each image in the dataset has been assigned an integral value between 0 and 4 on a scale from the mild to the severe disease, as shown in Table 1 for every component of the output vector.

Figure 3 below shows how images are distributed according to various DR scale.

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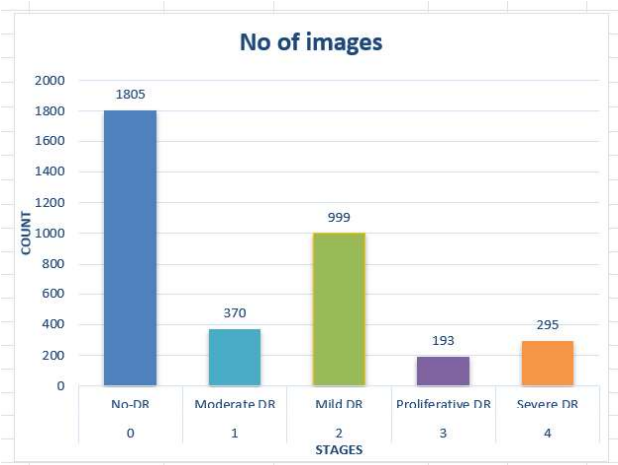

Fig.3: Distribution of Retinal Fundus images from APTOS 2019 dataset

The quality of the photographs in this dataset, which originated from various camera models and categories, was quite variable. Both the labels and the images contained noise. Some pictures had artefacts, such as out-of-focus areas or overexposed or underexposed areas. The current method for diagnosing DR is laborious and requires a trained eye specialist to examine digital colour images of the fundus of the retina. It can take human reviewers a day or two to submit their feedback, by which time it may be too late to use the results for any kind of follow-up, communication, or processing. Blindness in the world is 2.6% due to DR.

B. Methodology

Convolution Neural Networks are an artificial neural network type that achieves remarkable results in automatic feature extraction and classification. Deep CNNs also use ReLU (Rectified Linear Units) as transfer functions, which, because they do not disappear at extremes, facilitate effective training. Deep networks may easily be parallelized using GPUs because they contain numerous layers.

The pre-trained CNN model VGG-16, MobileNetV2, was utilised in the suggested method, and it was finetuned using the DR dataset. The model was trained to classify fundus pictures into five DR severity levels, from no DR to proliferative DR. In figure 4 below, the model of the suggested system is shown. From retina photos, CNN automatically extracts features. To refine the entire network, a last fully linked layer is added after the two layers used for feature extraction and selection.

The VGG-16 is a variation of the well-known VGG-Net convolutional neural network. 13 convolutional layers and 3 fully linked layers are among the layers that make up VGG-16. It assigns it to one of the 1000 classes after receiving a colour image with a size of 224*224 pixels as input. The network, which has 16 layers, is used to classify photos into several groups. The model has attained state-of-the-art performance and has excelled in a number of picture identification challenges, including the well-known ImageNet challenge. In order to extract complicated features from the input image, VGG-16 is an example of a deep learning-based architecture, meaning it has several layers and non-linear activation functions. This enables it to accurately distinguish objects, faces, and other features.

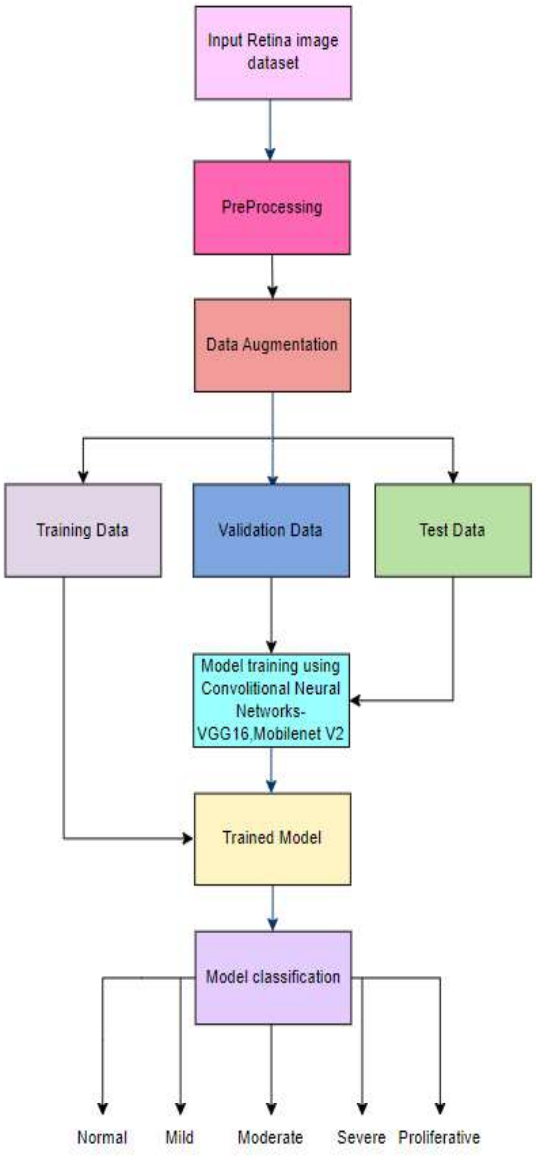

Fig.4: Proposed Classification Model

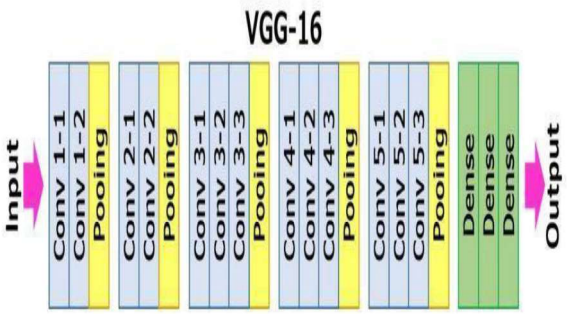

Fig.5: VGG-16 architecture [24]

As its name suggests, MobileNetV2 is a convolutional neural network architecture designed to excel on mobile devicesThe bottleneck layers are linked by residual connections, making use of an inverted residual structure. Non-linearity is introduced by light-weight depthwise convolutions applied to the intermediate expansion layer filters. The MobileNetV2 architecture consists of 19 additional bottleneck layers in addition to the first fully convolutional layer that contains 32 filters.

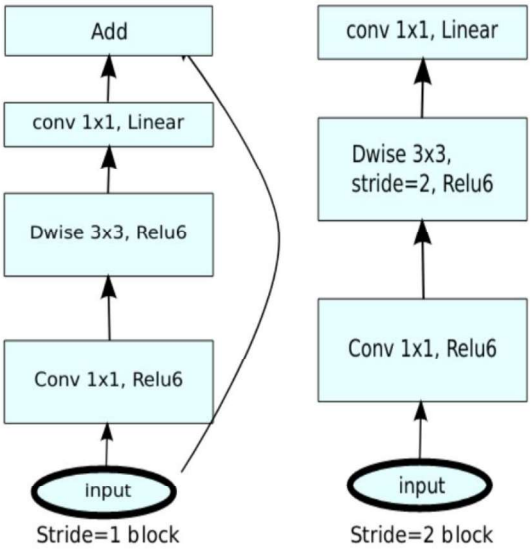

Fig.6: Architecture of MobileNetV2[25]

C. *Performance evaluation mesures*

Accuracy: Using positive and negative classes, the accuracy can be determined. Accuracy is then determined by dividing the number of right predictions by the total number of predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

Where TP-TruePositive,TN-TrueNegative,FP-False Positive,FN-False Negative.

IV. RESULTS AND DISCUSSIONS

We have proposed a classified model by using deep learning. More specifically, we built a model using VGG-16 and MobileNetV2 architecture and Kaggle dataset to train and test it. This method uses 2929 retinal fundus pictures for training and 733 for testing. The VGG-16 model was 90.05% accurate, while MobileNetV2 is 92% accurate. By using the Categorical Cross entropy loss function, the loss was kept to a minimum. With the help of the ADAM optimizer, training the model was quick and effective. The result is a number between 0 and 4 that shows the severity of diabetic retinopathy.

A.VGG-16 Results

The VGG-16 model classification's training and validation loss functions across 40 epochs are shown in the figure 7 below.The training and validation loss significantly reduces after the first epoch.

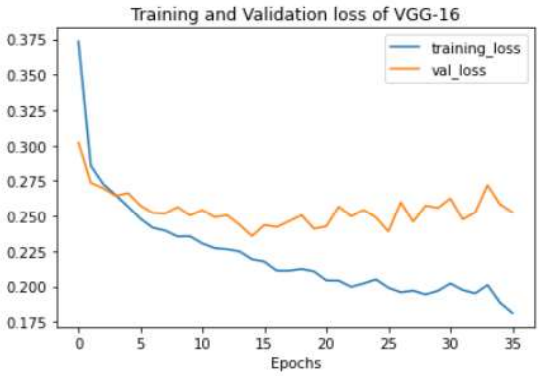

Fig.7: VGG-16 loss in the validation and training phases

VGG-16 maintains a constant 90% accuracy throughout all epochs in the validation stage; however, in the training phase, accuracy is not stable until epoch2.The training accuracy is around 91%.For VGG-16 the training accuracy is around 92.16% and validation accuracy is around 90.55% which is shown in Fig 8.

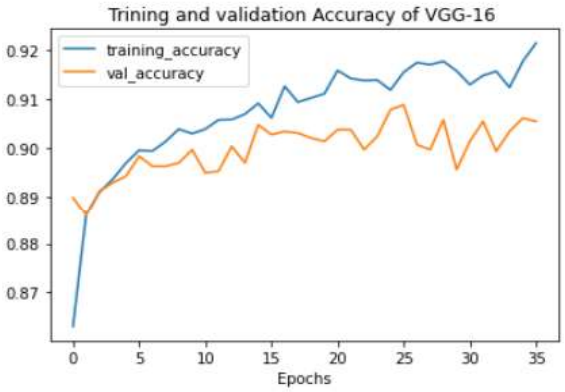

Fig.8:VGG-16 Accuracy in the training and valiadation stages.

The VGG-16 confusion matrix is depicted in the figure.It is clear from examining the VGG-16 model matrix that most predictions were made for Stage 0 (No-DR), while Stages 4 (Proliferative) and 5 (Severe) were not anticipated at all.

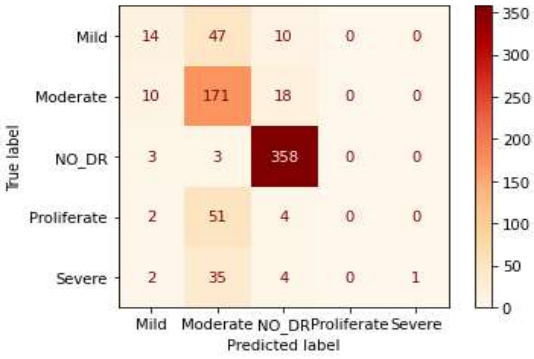

Fig.9: Confusion matrix of VGG-16

B.MobilenetV2 Results

The MobileNetV2 training and validation loss curve is depicted in Figure 10. The training and validation losses decreases significantly in the initial epochs. Figure 11 depicts the accuracy curve of Mobile NetV2 during both the training and validation phases. MobileNetV2's training and validation accuracy rise after the early epochs, as depicted in Figure 11. In the case of MobileNet V2, the training accuracy is 92.54 % and the validation accuracy is 91.64 %.

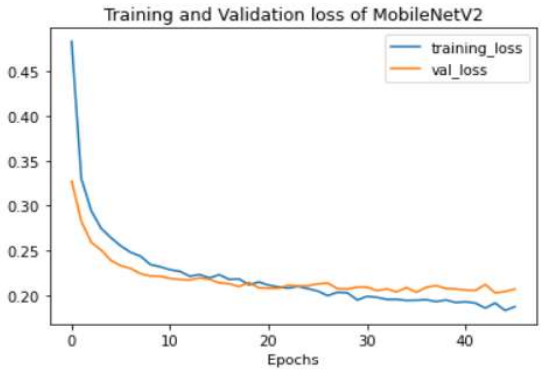

Fig.10: MobileNetV2 Loss in the validation and training phases

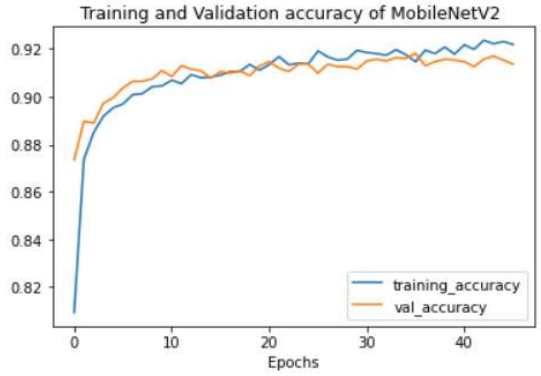

Fig.11: MobileNetV2 Accuracy in the validation and training phases

The performance of MobileNetV2 is described in the confusion matrix shown below in figure 12. Many predictions were made across all DR categories using the MobileNetV2.

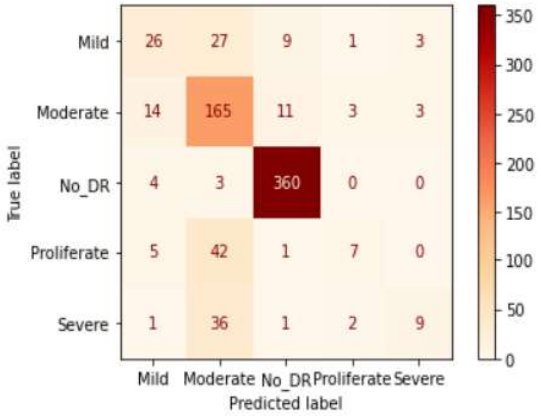

Fig.12: Confusion Matrix of MobileNetV2

Table III shows how the current study compares to similar work done in the past, based on the number of classes in the current study, which is five.

TABLE III: Comparison of Current study with previous works

Author	Year	classifier	Accuracy
Wang et al. [26]	2018	Alex net VGG-16 Inception V3	37.43% 50.03% 63.23%
Pratt et al. [27]	2016	CNN	75%
Current study	2023	VGG-16 MobileNetV2	90% 92%

V. CONCLUSION

According to numerous polls, a person with diabetes has about 30% probability of developing diabetic retinopathy (DR). From mild to severe, and then PDR, there are various stages of DR . If the problem is not detected while it is in its early stages, it may ultimately lead to blindness and cause other visual impairments such as floaters, poor vision, and other visual impairments.It is time-consuming and challenging to manually diagnose these photos, which calls for highly qualified professionals. It has been claimed in the research that computer vision-based technologies might be used for automatically identifying DR and the many phases it goes through. The primary deficiency of previous models is their inability to categorise early stages of DR, hence we concentrated on doing so in our article. For the purpose of identifying and categorising the various stages of the DR in colour fundus images, we used two pretrained networks, such as the VGG-16 and MobileNetV2. We used the APTOS 2019 dataset, which contains the most comprehensive collection of publicly available fundus images, to train and evaluate our model. According to the findings, MobileNetV2 outperforms VGG 16 and is also capable of detecting all DR phases.

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