DIABETIC RETINOPATHY DETECTION USING TRANSFER LEARNING BASED DEEP LEARNING MODEL

[1]L.V.Rajani Kumari, [2]D.Ramesh Reddy, [3]Chetah.Varsha

[1]Associate Professor, Department ECE ,VNR Vignana Jyothi Institute Of Engineering &Technology, Hyderabad, Telangana 500090
[2]Assistant Professor, Department ECE ,VNR Vignana Jyothi Institute Of Engineering &Technology, Hyderabad, Telangana 500090
[3]Mtech, Department ECE ,VNR Vignana Jyothi Institute Of Engineering &Technology, Hyderabad, Telangana 500090

Abstract:
Diabetic Retinopathy (DR), an eye condition that mostly affects people with diabetes, is one of the main causes of adult blindness. Eighty percent of patients with DR have been shown to have chronic diabetes over a period of 10 to 15 years. As the disease progresses, it may result in a permanent loss of vision. Early detection allows for an early diagnosis of DR. This work focuses mostly on applying deep learning (DL) and transfer learning approaches to diagnose diabetic retinopathy. The Messidor 2 dataset, which includes 1748 macula-centered eye fund images, of which 1744 are labeled and 4 are not labeled, is considered in this study. There are two classes in the labeled data: DR0 (fundus image without diabetic retinopathy) and DR1 (fundus image with diabetic retinopathy). Using the principles of transfer learning, the pre-trained models ResNet18, MobileNet-V2, and GoogleNet are refined and optimized via three distinct optimizers: ADAM, RMSprop, and SGDM. The developed models provide an accuracy of 98.9% for ResNet18 models, 74.4% for MobileNet-V2, and 68.1% for GoogleNet. The developed models show better performance than the existing algorithms.
Keywords: Convolutional Neural Network(CNN), DeepLearning(DL), Optimizer, Transfer learning, Augmentation, Adaptive Moment Estimation(ADAM), Root Mean Square Propagation(RMSprop), Stochastic Gradient Descent with Momentum(SGDM), MoblieNet-V2, GoogleNet, ResNet 18, Diabetic Retinopathy (DR)

I.INTRODUCTION

The extremely high blood sugar levels seriously damage the blood vessels in the retina. The eye's blood vessels start to leak fluid, which causes the macula to enlarge or thicken and block blood flow. On the retina, there can occasionally be an aberrant proliferation of new blood vessels. A permanent loss of vision can result from any of the disorders mentioned above. This condition causes the cases of retinopathy dieting. One of the main causes of blindness in the western world is diabetic retinopathy (DR) [1][2]. Diabetes retinopathy is becoming more and more difficult to diagnose manually due to the growing number of diabetes patients and the lack of access to specialists in optical health [3]. The advent of deep learning techniques, particularly CNN, which are frequently employed in the field of DR detection, offers one option to get over this restriction [4] [5]. In deep learning, CNN pre-trained models are considered to identify the DR. The deeper layer models, like ResNet18, GoogleNet, and MobileNet-V2 DL models, are taken for the data extraction from the fundus image and to train the model. To improve the developed model performance, optimization methods ADAM, RMSprop, and SGDM are used to identify the DR0 (normal) and DR1 (abnormal) states of diabetic retinopathy using a classification model.

II. METHODOLOGY

The considered dataset contains both normal and abnormal DR[6], which are divided into 3 datasets: training, validation, and testing datasets[7].Original fundus images of both training and validation datasets are processed using image augmentation methods, which are random rotation, random scaling, horizontal flip, and vertical flip used to generate several versions of an image by arbitrarily altering its size. This method works well in deep learning applications when training image recognition algorithms requires a lot of labeled data [8].

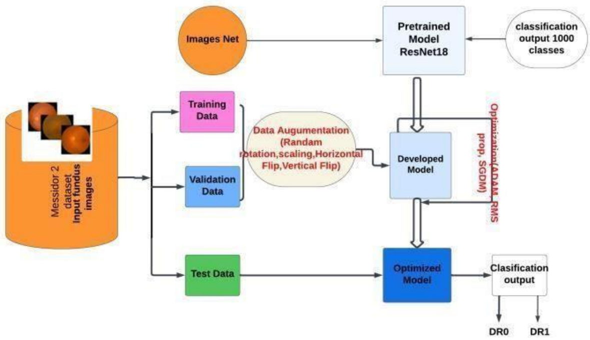


Fig:1 Proposed methodology for detection of diabetic retinopathy

Figure 1 is the complete overview of DR detection using CNN models step-by-step.

The pre- trained models ResNet 18, GoogleNet, and MobileNet-V2 are fine-tuned by using the concept of transfer learning [9].

Resnet 18: A deep learning model called a residual neural network uses layer inputs to teach its weight layers residual functions. A residual network is a network with skip connections that combines by addition with the layer outputs after performing identity mappings [10]. Its gates are opened by highly positive bias weights, operating in a manner akin to a highway network [11].

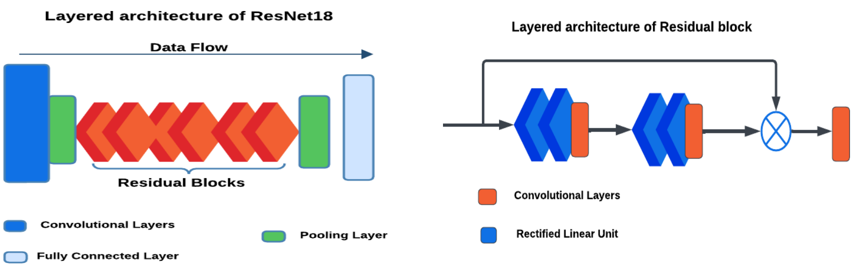


Fig:2 ResNet 18 Architecture and Residual block

Figure 2 shows the original ResNet-18 design has eighteen layers in total, consisting of one fully connected layer, seven convolutional layers, and one extra softmax layer for classification tasks. 3 x 3 filters are used by the convolutional layers, each convolution layer as a residual block. Residual block is the term used to describe the subnetwork [6]. A sequence of residual blocks is stacked to create a deep residual network. Let x be the input to this subnetwork, and let H(x) be the underlying function and F(x) be the internal function.

$$\mathrm{F}(x) = H(x) - x \qquad (1)$$

where y is the output of sub network

$$H(x) = F(x) + x \qquad (2)$$

Which computes $$yt = ((xt) + (xt)) \qquad (3)$$

During back propagation through time, this becomes

$$(x) = F(x) + x \qquad (4)$$

MobileNet-V2: An improvement to the original MobileNet model is MobileNet-V2. This model is also noteworthy for its ability to balance model size and accuracy, which makes it perfect for devices with limited resources. Two key concepts are added to MobileNet-V2: it uses inverted residual blocks with bottlenecking features.

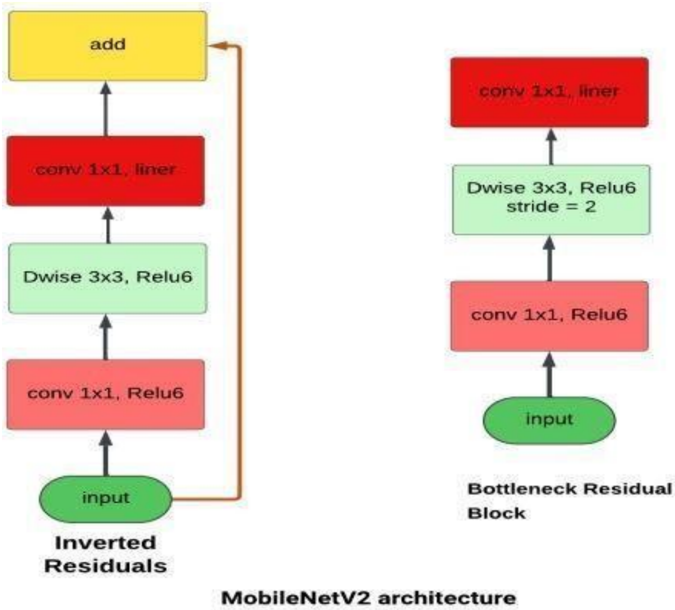


Fig:3 MobileNet-V2 Architecture

Figure 3 shows a perspective of two MobileNet-V2. It starts with a complete convolution layer with 32 filters and has 19 residual bottleneck layers.

GoogleNet: GoogleNet is a convolutional neural network with 22 layers that differs from other cutting-edge models like ZF-Net and AlexNet. It employs a variety of techniques, including global average pooling and 1×1 convolution, to enable the creation of deeper architecture.

PREPROCESSED DATA AND GRADCAM HEAT MAPS:

Grad-CAM (Gradient-weighted Class Activation Mapping) solves the problem of interpretability in these intricate models and provides a visual explanation. Figure 4 shows the Grad-CAM heatmaps, fundus image, and preprocessed images.

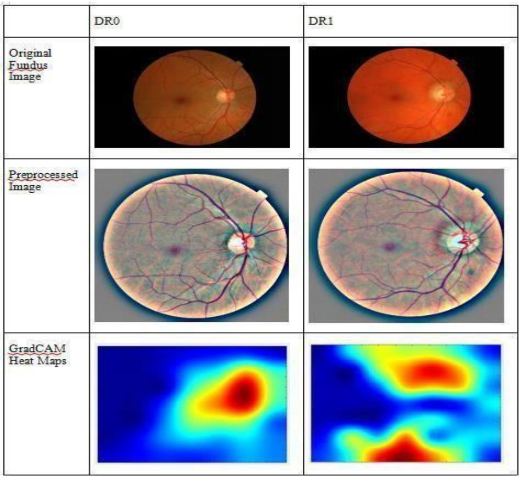


Fig:4 Comparison between normal and abnormal using GradCAM Heat map

Performance Metrics: A confusion matrix is a matrix that presents a final model's performance on a set of test data in summary form.

Table: 1 Confusion matrix for binary classification

Prediction Class	True class	Class1	Class2
Class1		Tp	Fp
Class2		Fn	Tn

$$\text{Precision} = \frac{\text{Tp}}{\text{Tp+Fp}} \qquad \text{Specificity} = \frac{\text{Tn}}{\text{Tn+Fp}} \qquad \text{Recall} = \frac{\text{Tp}}{\text{TP+Fn}}$$

$$\text{Accuracy} = \frac{\text{Tp+ Tn}}{\text{Tp + Fp+Tn+Fn}} \qquad F-\text{Score} = \frac{2*\text{Tp}}{\text{Tp + Fp+Tn+Fn}}$$

Tp: true positive, Tn: true negative, Fp: false positives, Fn: false negatives.

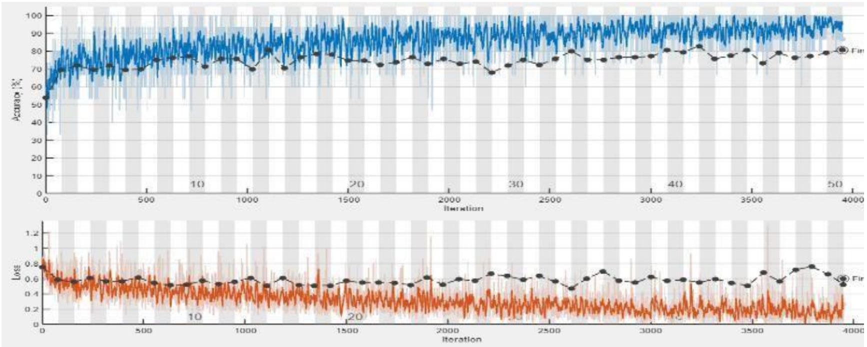
III.RESULTS AND DISCUSSIONS

Table 2 shows the parameters considered for fine-tuning ResNet18, MobileNet-V2 and GoogleNet models.

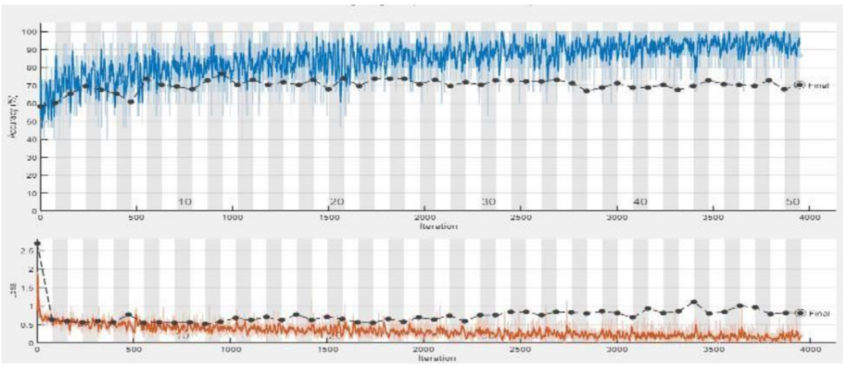
Table: 2 Parameters considered for fine-tuning ResNet18, MobileNet-V2 and GoogleNet models.

Tested parameter of ADAM optimizer	Models		
	ResNet18	MobileNet-V2	GoogleNet
Maximum epochs	20	50	50
Initial learn rate	0.0001	0.0001	0.0001

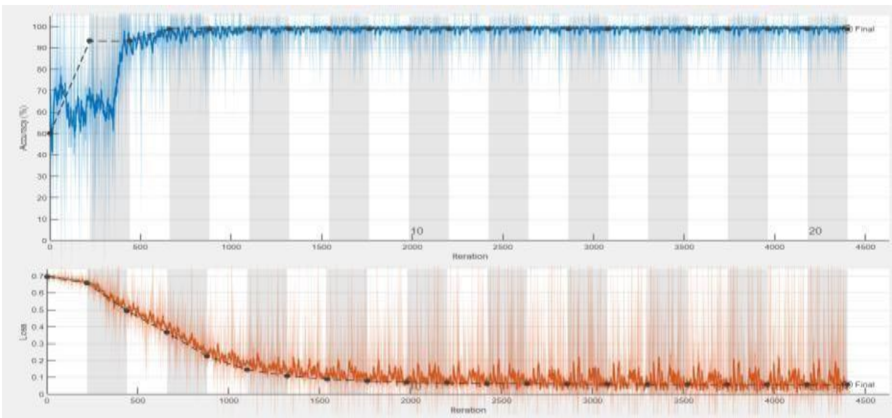
Training time	5 min 1 sec	30min 18sec	25min 25sec
Validation Accuracy	97.98	80	70.33
Iteration	4400	3950	3950



a) Accuracy and loss function of MobileNet-V2



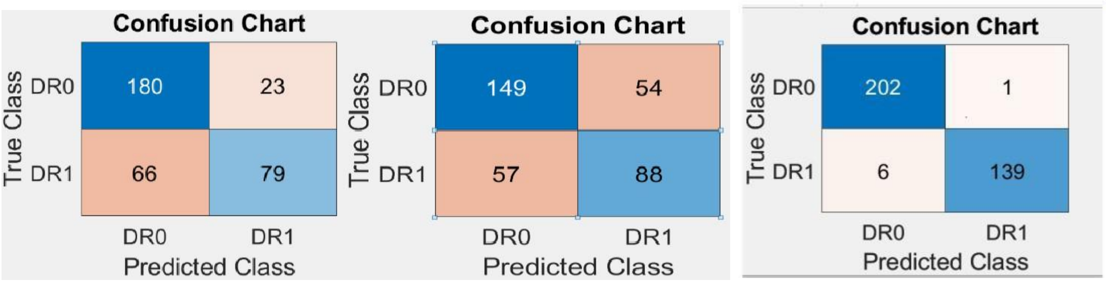
b) Accuracy and loss function of GoolgeNet



c)Accuracy and loss function of ResNet 18

Fig:5 Accuracy and loss function

Figure 5 shows the accuracy and loss function of different models MobileNet-V2, GoolgeNet, ResNet 18.



a) MobileNet-V2 model b) GoogleNet model c)ResNet18

model Fig:6 Confusion chart.

Figure 6 shows the confusion charts of MobileNet-V2 , GoogleNet and ResNet18.Table 3 shows the performance of models MobileNet-V2 , GoogleNet and ResNet18.

Table: 3 Performance measures of models.

Performance Measure	Models		
	MobileNet-V2 (%)	GoogleNet (%)	ResNet18 (%)
Accuracy	74.4	68.1	98.9
Specificity	54	60.6	95.8
Recall	88	73.3	99.5
F-score	80	72.8	98.2
Precision	73	72.3	97.1

IV. Comparisons of State of Art Techniques:

The performance of the developed models is compared with the existing models in the literature. Table 4 shows the comparison of the developed models with the existing algorithms. From the experimental results, it is clearly shown that ResNet18 outperforms the existing model's accuracy of 98.9%.

Table: 4 Comparison of our developed models with state-of-the-art techniques.

Study	Type of dataset	Methods	Specificity (%)	Accuracy (%)
Othmane Daanouni .et.al.[12]	OCT images	MobileNet	_	87

Dolly Das.et.al. [13]	EyePACS fundus image	DenseNet201 (training)	_	99.5 (training)
Dong .et.al. [14]	2693 images	InceptionV3 -VGG-16 based CNN	_	96.11
Harry Pratt.et.al. [15]	Kaggle 80,000 images	CNN	95	75
Yasashvini R.et.al. [16]	Kaggle	DenseNet 2.1	_	96.22
Proposed	Messidor- 2	MobileNet-V2 , GoogleNet ResNet 18	54 60.6 95.8	74.4 68.1 98.9

V. CONCLUSION

Transfer learning-based deep learning model used to detect diabetic retinopathy. Fine-tuned MobileNet-V2 achieved 74.4% accuracy among all models, followed by GoogleNet with 68.1% accuracy and ResNet18 with the greatest accuracy of 98.9%. From the experimental results, ResNet 18 provides a higher performance than other implemented algorithms, MobileNet-V2, GoogleNet, and existing algorithms. In the future, examining the effects of various hyperparameters and architectural modifications may improve the overall efficiency of other models.

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