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An Evaluation of Pre-Trained Deep Learning Algorithms for Diabetic Retinopathy Disease Identification Using Retinal Fundus Images

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Abstract: A persistently elevated blood sugar level can lead to diabetic retinopathy (DR), an eye disorder that damages retinal tissue by obstructing and bleeding retinal capillaries. Usually, it causes blindness. The risk and severity of DR can be reduced by early identification. Diabetic retinopathy is difficult to detect and predict with reliability and accuracy. In this paper, a completely accurate deep learning model for Diabetic Retinopathy identification is developed. Utilizing a transfer learning (TL) strategy, pre-trained models with a pooling layer, dense layer, and suitable dropout layer at the bottom were used, including ResNet50, InceptionV3, Alexnet, and VGG19. To minimize overfitting, data augmentation along with regularization were carried out. The DL systems had been trained and evaluated on the Asia Pacific Tele-Ophthalmology Society (APTOS) datasets. The robustness of the chosen models was demonstrated by the calculation of testing accuracy and performance metrics, including precision, recall, and F1 score. The AlexNet model shows its greatest testing accuracy at 98.66%. Additionally, the obtained evolution metrics reinforced our obtained results. Additionally, AlexNet has a limited number of the layers, which reduces training time as well as computational complexity.

Keywords: *Diabetic Retinopathy, Transfer Learning, Ensemble Learning, Augmentation, Retinal Images*

1. INTRODUCTION

Excess blood glucose is produced by the human body in diabetes, also referred to as diabetes mellitus [1]. It is the fourth most common cause of mortality and a chronic illness that affects everyone [2]. The main reason for the increase in blindness worldwide is diabetic retinopathy. Records show that up to 415 million people globally suffer from diabetes. Diabetics should undergo screening annually to prevent blindness. Examining the fundus picture and determining the illness's severity is a standard procedure for identifying diabetic eye disease. According to the category of retinopathy, the lesions are microaneurysms, haemorrhages, hard exudates, etc., which are signs of eyeball bleeding exudation, the severity varies. The cooperation between an ophthalmologist and a diabetic care physician is improving. In places with a shortage of physicians, diabetes patients have a limited opportunity to get fundus examinations. Additionally, the number of ophthalmologists qualified to diagnose and treat diabetic retinopathy is insufficient. Even in highly developed nations, the level of dispensary ophthalmologic monitoring of diabetic patients is still inadequate today.

Manually detecting DR from retinal pictures is problematic because it takes a lot of time and there aren't many professionals. Therefore, it would be beneficial to develop an automated diabetic retinopathy identification system that can function without a physician's assistance in order to address this issue. In order to identify diabetic retinopathy, a number of studies have used deep convolutional neural networks (CNNs) [2]. Nevertheless, GoogleNet [3], VGGNet [4], and very deep CNN models were used in the suggested models. Although there is still need for significant improvement, these efforts attained good accuracy. Therefore the current study concentrated on using an accurate, end-to-end CNN-utilized hybrid model that leverages transfer learning.

Numerous conditions, such as nerve damage, heart disease, stroke, foot problems, gum disease, and more, have been linked to diabetes [1]. The difference between a normal retina and DR-affected retina is shown in Figure 1.

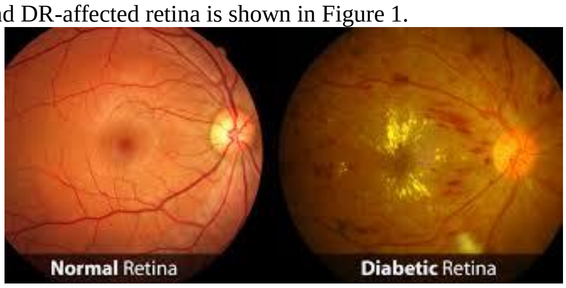

Figure 1: Normal retina and DR-affected retina

The report by the International Diabetes Federation (IDF), 336 million people worldwide are estimated to have diabetes, and by 2030, that number is predicted to rise by 7.7% [3, 4]. The diabetes condition called diabetic retinopathy (DR) causes the retinal blood vessels to expand and leak blood and fluid [5]. The Mayo Clinic [6] states that visual spots, colour impairment, blurred or fluctuating vision, and, in extreme situations, total vision loss in one or both eyes are common signs of DR. The micro-vessels within the retina, which are essential for feeding the retinal tissues, get obstructed by persistently elevated blood sugar values.

Diabetic retinopathy is categorized as either "non-proliferative diabetic retinopathy (NPDR) or proliferative diabetic retinopathy (PDR)" based on structural variations in colour fundus images. Neovascularization and vitreous hemorrhage are signs of PDR, whereas hard exudate, microaneurysm, soft exudate, and hemorrhages are some of the symptoms of NPDR [7].

Therefore, trustworthy auto DR screening techniques that use artificial intelligence to identify DR are required. Through an ensemble of various transfer learning models, we have created an effective model in this work for DR detection. It has helped produce a fantastic result. The following sections show the literature survey, proposed methodology, results and discussion and finally conclude in this paper.

2. LITERATURE SURVEY

Numerous studies on the automatic identification of diabetic retinopathy have been published in the literature review. The techniques employed throughout its entirety of automatic diabetic retinopathy detection are roughly divided into two classes. Deep learning based diabetic retinopathy diagnosis uses automatic feature extraction, while the first uses typical machine learning methods that require additional feature extraction approaches employing image processing.

The KNN algorithm was suggested by [8] for the identification of diabetic retinopathy. They used image processing to first extract features, which they then sent into KNN. Their accuracy on the local dataset was 87%. Using image processing, [9], presented a novel feature extraction technique called dynamic feature shape. For classification, they employed decision trees and random forests. The sensitivity score of their approach was high.

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A diabetic retinopathy diagnosis method based on convolutional neural networks was proposed in [10]. Thirteen CNN layers have been employed. To address the issue of data imbalance, they used data augmentation techniques. They reported 95% sensitivity on 5000 images of test data from the EyePACS dataset.

The authors [11], classified retinal images using residual neural networks. They built an end-to-end framework using the EyePACS DR dataset. Quadratic weighted kappa (QWK) is an evaluation metric used to assess the performance of the model [12]. The kappa score they reported was 0.5104. ResNet was used in [13] for the classification of images of diabetic retinopathy. They expanded ResNet's intermediate hidden layers. These unique layers were added, and the model's performance was enhanced. The EyePACS DR dataset was used to train the model. The quadratic kappa value weighed of 0.73 was attained by them.

The retinal pictures were classified in [14] using GoogleNet and AlexNet. The retinal image was first pre-processed before being sent to GoogleNet along with AlexNet. They trained with tested the model utilizing the EyePACSDR datasets. Using GoogleNet and AlexNet, they reported AUC scores of 0.78 and 0.68, respectively. Transfer learning was employed in [15] to detect diabetic retinopathy. They made use of pre-trained models of the AlexNet and GoogleNet. The Messidor1 diabetic retinopathy datasets was used to build the model. On the Messidor1 dataset, the GoogleNet greatest accuracy was 66.03%.

The diagnosis of diabetic retinopathy (DR) using fundus pictures has been the subject of numerous deep learning-based studies. Some of the current research projects are covered in this part. The authors [16] used two CNNs using VGG16 and CNN to classify diabetic retinopathy or non- fundus images based on the chances of lesion patches. For training, the DIARETDB-1 dataset was used. Tests were conducted using the, IDRiD, DDR, Messidor, DIARETDB0, Kaggle and Messidor2 datasets. The Messidors dataset produced the better results of sensitivity of 0.94 as well as an AUC of 0.912.

The authors [17] model uses three CNNs to classify a fundus image dataset as referable and non-referable DR. The Adaboost technique was utilized to merge the scaled, enhanced, augmented fundus images before training.

The Adam optimizer was utilized to change the network weights, and the system have an accuracy of 82.21% and an AUC of 0.946. The authors [18] used CNN with 10 convolutional layers, 8 max-pooling layer, 3 fully connected layer, and a softmax classifier to Kaggle fundus pictures into five classes based on the DR severity levels. To lessen overfitting, L2 regularization with dropout techniques were applied for coloring fundus images that had been normalized and shrunk. Results from the model showed 30% sensitiveness, 75% accuracy, and 95% selectivity.

In [19], suggested a transfer model for learning that avoided overfitting by using a dropout layer and InceptionV3, a pretrained model. On the Kaggle dataset, the model's training accuracy was 98.6%. The precision of the model is 86.6% when there is no DR, 62.5% when it is light, 66.6% when it is modest, 57.1% when it is severe, and 42.8% when it is PDR.

In order to analyze diabetes picture categorization method the [20] used,GoogleNet ,VggNet, AlexNet and ResNet using transfer learning and tuning of hyper-parameters. The best precision of 95.68 was supplied by VggNet-s via hyper-parameters. The authors [21] used the VGG-16 model using a pre-trained neural network and fine-tuning in order to classify the severity of DR. Learn-rate scheduling, dropout layers, batch normalization, and data augmentation were applied to high-quality images to achieve a 74% accuracy rate.

A combination of the following: SVM, KNN, and naive Bayesian models was proposed by [22] and used on the MESSIDOR fundus dataset. Its accuracy was 92%. Robiul Islam et al. created a deep learning system that integrated transfer learning using VGG16 [23]. APTOS Blindness Detection, a new Kaggle dataset, reduced training time and yielded a typical accuracy of 0.9132683. the authors [24] measured diabetic retinopathy (DR) using CNN (VGGnet) and obtained an accuracy of 95.41%.

Similarly to the suggestion in [25], Inception-ResNet-v2 was first trained using transfer learning, and then a custom block of CNN architectures was constructed on top of Inception-ResNetv2 to build the hybrid model. The model's test accuracy on the Messidor1 and APTOS datasets is 72.33% and 82.18%, respectively.

The authors [26] used the publicly available Kaggle dataset of retinal pictures to train an ensemble of five deep Convolution Neural Network (CNN) models and achieved an accuracy of 80.70 percent. The authors [27] developed a novel diabetic retinopathy monitoring model that employed the Contrast Limited Adaptive Histogram Equalization technique used to enhance the image quality and reliably equalize intensities.

3. PROPOSED METHODOLOGY

This study provides pretrained deep learning algorithms for diabetic retinopathy diagnosis from retinal fundus images. These tests were conducted using the APTOS dataset. The entire procedure and experimental setup are covered in full in the section that follows Figure 3 shows the entire workflow of our suggested approach. Image the pre-processing process augmentation of data, ResNet50, InceptionV3, Alexnet, and VGG19 are its four steps. Prediction, and transfer learning. First, we pre-processed the colour retina image by cropping, blurring, and applying a bounding box. After that, we scaled it to a specific size that works well with deep learning models. In order to fine-tune the model on an enhanced train data set, we next used the ResNet50, InceptionV3, Alexnet, and VGG19 models along with an extra layer. Lastly, we will forecast the class using the softmax layer's prediction score.

3.1. Dataset Selection

The dataset is split into training, validation, and testing groups for APTOS 2019 Blindness Detection [28] of the 3662 samples gathered from various people in rural India, the Asia Pacific Tele-Ophthalmology Society 2019 Blindness Detection (APTOS)dataset is present. The dataset was organized by the Aravind Eye Hospital in India. The fundus photos were gathered over an extended period of time in a variety of settings and scenarios. The APTOS samples are separated into five groups according on the scale system: proliferative DR, mild DR, moderate DR, severe DR, and no DR.

3.2. Image Pre-processing

The pixel sizes of their photos vary. Since the model cannot accept input of varied dimensions, we wish to use photographs of the same size for training. Therefore, we must first preprocess the photograph and adjust its size. As shown, we have completed the three preprocessing procedures of blurring, obtaining the bounding box coordinates that indicate the cropping, and resizing. We resize the pictures to 224x224x3 and 350x350x3 sizes. After that, we separate them into datasets for training, validation, and testing, assigning 80%, 10%, and 10%, respectively. In order to make sure that every picture value lies inside the range [0, 1], we next normalize the training sets (xtrain) and (ytrain) by dividing each by the standard deviation. Using one-hot encoded vectors for (ytrain) and (ytest), we define five classes that correspond to the levels of DR: [1, 0, 0, 0, 0, 0, 0] denotes the Normal class, [0, 1, 0, 0, 0] denotes the Moderate class, and so forth. The preprocessed retinal images are displayed in Figure 2.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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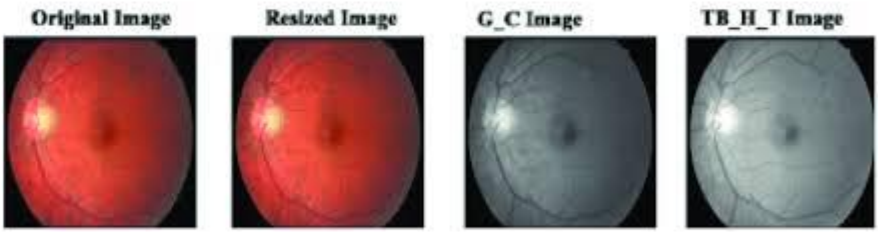

Figure 2: Pre-processed retinal fundus image

3.3. Data Augmentation

Using various geometric forms of transforms like shift, zoom , flip, channel shift, , rescale, rotate, etc., are utilized. we employed image augmentation as a crucial operation to be applied to both training along testing datasets in order to decrease overfitting, increase the number of fundus to 8000, and improve the system's accuracy.

3.4. Convolution Neural Networks

In order to classify images of diabetic retinopathy (DR), we built a Convolutional Neural Network (CNN), which is generally considered to be state-of-the-art for a variety of image classification tasks. The following layers make up our suggested CNN design. The convolutional layer is used to extract information from pixel-based input images. For this, we use sixteen 3x3 kernels.

- The output of the previous layer is normalized across the batch size by the batch-normalization layer.
- Max Pooling Layer: Uses a 2x2 window to reduce the output image's dimensions.
  Dropout Layer: During training, some neurons are randomly removed to prevent overfitting.
- Flatten Layer: To transfer the output to the following layer, it is converted to a one- dimensional (linear array).
- Dense Layer: A completely networked layer used for the last five-class classification. The nonlinear activation function "SoftMax" comes after it.

3.5. Pre-Trained Models

Transfer learning (TL) is an automated learning methodology that uses a learning strategy developed for one assignment as the foundation for a model on another project. The previously trained model is applied to a new challenge. TL's primary advantages are shorter training times, better neural network performance, and a lack of data requirements. Resnet50, VGG19, VGG16, AlexNet, and Inceptions are among the most often used pre-trained models for TL. ResNet50, InceptionV3, VGG19, and Alexnet were used as pre-trained models in this study. The AveragePooling2D layer, SoftMax is a layer, Dense layer having three categories, and Dropout layer take the position of the classification layer in each model. A dropout value of 0.24 was used in order to prevent overfitting. With a learning rate of 0.002, categorical cross-entropy, and a batch size of 20, with the Adam optimizer was used to fit all the models. With a 98% accuracy rate, Alexnet outperformed all the pre-trained models; other networks also fared well and were selected for learning. The Proposed methodology is shown in Figure 3. The total number of parameters, trainable parameters, NonTrainable Parameters of different models are shown in Table 1.

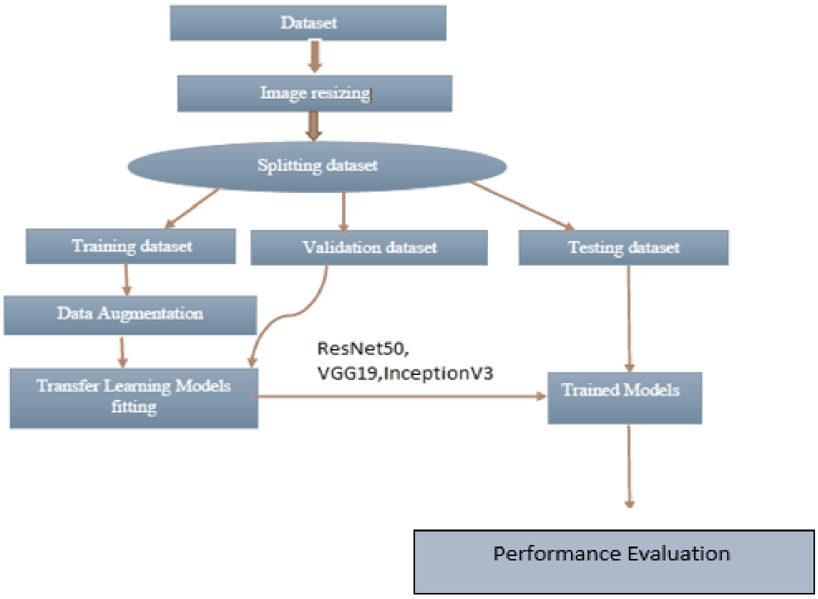

Figure 3: Proposed methodology

Table 1 : Displays the models' trainable parameters.

ne of the Pre Trained lel	l Number of ameters	nable Parameters	Trainable Parameters
net50	05,771	2	02,780
G16	15,411	2	24,312
Net	25,410	3	024,412
G16	25,312	6	,024,344
ptionV3	25,402	6	,024,43

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Vol. 36 Issue 1s, 2026, Pages: 305-309

4. RESULTS AND DISCUSSION

Various pre-trained transfer learning architectures are used in this work to detect diabetic retinopathy. It was run on a GPU-equipped GoogleColab. Average Pooling, dropout, and Dense layers were added beneath the foundation model of various pre-trained models, including DesnseNet50, InceptionV3, VGG19, and Alexnet. Several pretrained deep learning models' training datasets were subjected to data augmentation using the hyperparameter tweaking in Table 3. For these models, the metrics F1-score, precision, recall, and accuracy are calculated. The precision, recall, accuracy, and F1-score of the ResNet50 model are 93.32%, 92.21%, 94.54%, and 93.32%, respectively. Likewise, InceptionV3 displays 92.22%, 95.23%, 94.21%, and 95.21%, whereas VGG19 yields 96.32%, 95.21%, 97.32%, and 97.54, respectively. The state of art performance was given by the Alexnet, has 98.22%,97.23%,98.21% and 98.66 respectively. The Precision, Recall,Accuracy,F1 score of the pre trained models are shown the Table 1.Theperformance results of the models are visualized in the Figure 4.

Table 2: The Precision, Recall , Accuracy, and F1 score of the pre-trained models

S.No	Training set				
	Pre trained Models using Deep Learning Technique	Precision(%)	Recall(%)	Accuracy(%)	F1 score(%)
1	ResNet50	93.32	92.21	93.32	94.54
2	InceptionV3	92.22	95.23	94.21	95.21
3	VGG19	96.32	95.21	97.32	97.54
4	Alexnet	98.22	97.23	98.21	98.66

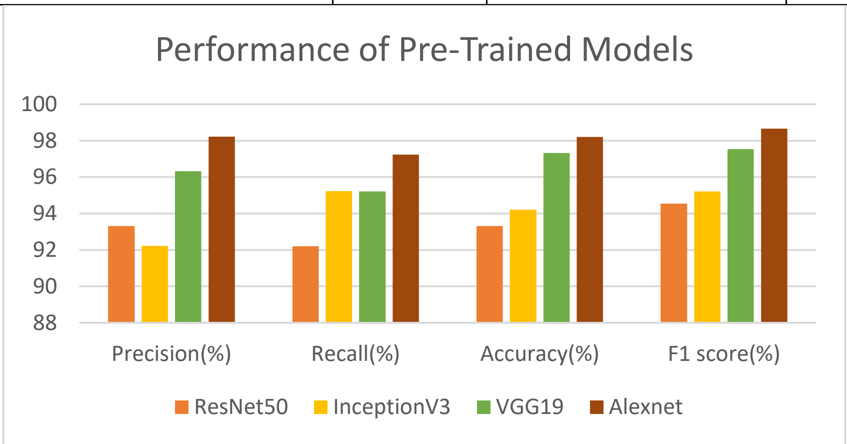

Figure 4: Model Results

Figure 5 shows the AUC curve of the deep learning models with probabilities and Figure 6 displays the AUC of the deep learning models.

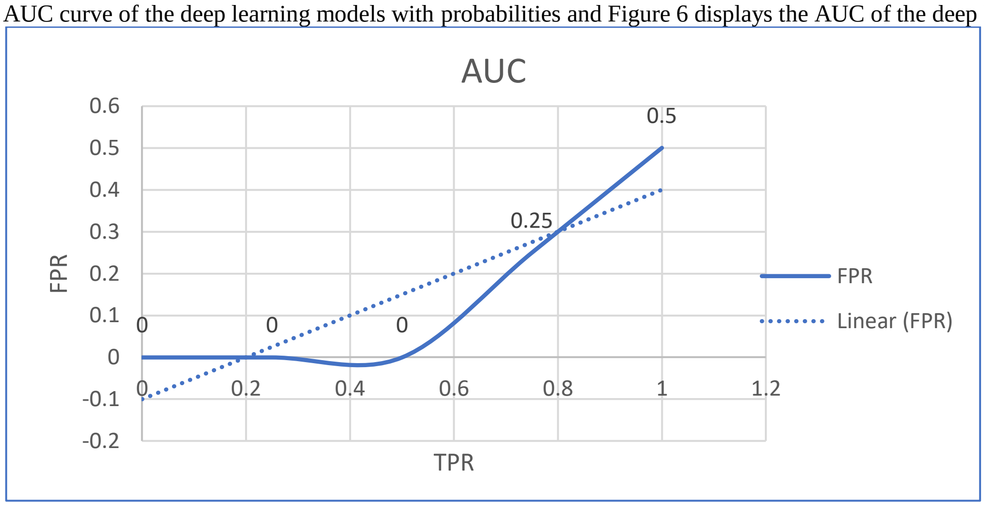

Figure 5: AUC for the models

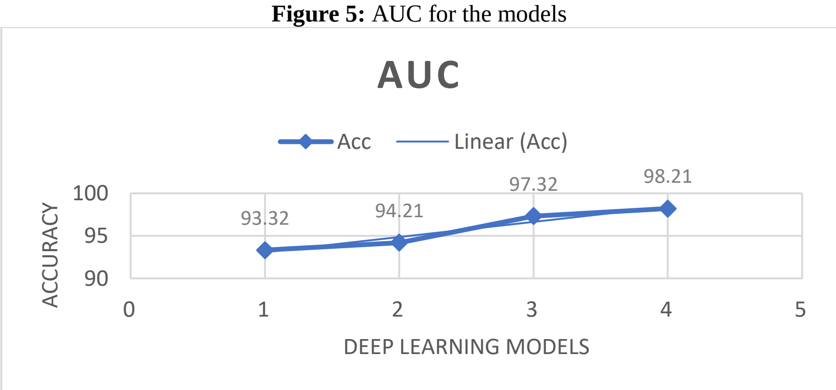

Figure 6: AUC of models with the Accuracy

4. CONCLUSION

In addition to saving ophthalmologists time and money, automated screening technologies speed up patient treatment by drastically cutting down on the amount of time needed to make diagnosis. Early DR detection is made possible in large part by automated DR detection systems. In our work, the Alexnet architecture yields the highest accuracy of 98.66% among the different TL architectures. The Alexnet is displaying more than the other models. Our work has relied heavily on data augmentation, parameter adjustment, the Average Pooling layer, and the dropout layer at the bottom of the pre-trained model. Patients may be able to start taking preventative measures right away if diabetic retinopathy is accurately diagnosed at the right time. Pre-processing of the data has been neglected. However, it is a crucial stage in deep learning. The degree of severity and further signs of eye conditions are not included. Future iterations of this study will take into account all of the constraints and be evaluated using actual data from the field.

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