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A HYBRID MODEL FOR DIABETIC RETINOPATHY DETECTION USING FUNDUS IMAGES OF THE EYE

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Abstract— **A medical disorder called diabetic retinopathy (DR) affects people with long-term diabetes. Vision impairment may result if a diagnosis is not made early enough. The major cause of DR in diabetic people is high blood sugar. Since DR can damage the retina, resulting in structural changes including Microaneurysms (MAs), Exudates (EXs), Hemorrhages (HMs), and additional blood vessel development, manual identification of DR is challenging. A hybrid approach is proposed for the detection and classification of diabetic retinopathy in eye fundus images. Transfer learning (TL) is used to extract features from pre-trained Convolutional Neural Network (CNN) models, which are then combined to create a hybrid feature vector. SVM classifier get this feature vector in order to categorize fundus images in binary and many classes. Multiple measures are used to gauge system performance, and the findings are contrasted with more contemporary methods of DR detection. The suggested technique significantly boosts fundus image DR detection ability. The suggested improved technique has the maximum accuracy for multiclass classification (89.29%) and binary classification (97.8%).**

Keywords—Diabetic retinopathy, hybrid deep learning features, fundus images, transfer learning.

I. INTRODUCTION

Diabetes Mellitus (DM) is a category of illnesses where the body develops excessive blood sugar levels. High blood sugar levels can be caused by a number of factors, such as inadequate insulin synthesis or insufficient cell responsiveness to insulin [1]. The World Health Organization (WHO) anticipated an increase in DM in the near future[2]. One problem brought on by diabetes is DR. Until the condition has progressed significantly, it mostly goes undiagnosed. Therefore, it must be detected early in order to avoid visual loss [3]. The veins inside the retinal tissues are impacted by the higher sugar level. A medical imaging method called a fundoscopy is used to photograph the retina's internal architecture [4]. Red lesions like Microaneurysms (MA) and intra-retinal hemorrhages are among the several abnormalities brought on by DR in the eye. Aside from these, exudates (EX) and cotton-wool spots are other white lesions that develop in the eye as a result of DR. An extremely small aneurysm or swelling on the side of a blood artery is known as a Microaneurysm (MA) [5]. Because of the weakened capillary walls caused by these tiny aneurysms, blood vessels may rupture and release blood. Hemorrhages [6] surrounding the blood vessels inside the retina are brought on by the blood that leaks from a microaneurysm.

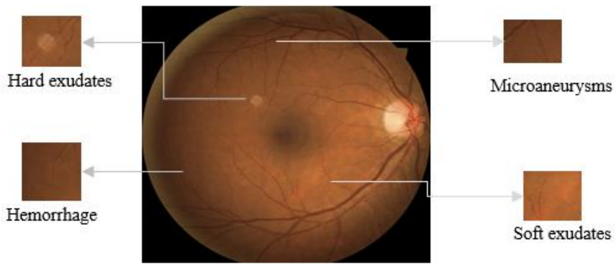

Figure 1. The category of abnormality present in a fundus image.

The above figure shows the category of abnormality present in a fundus image of a patient with diabetic retinopathy.

Diabetes is not the sole factor contributing to retinal vascular damage. Numerous retinal problems can also be brought on by obstructive sleep apnea syndrome and an excess of reactive oxygen species during active retinal utilization [7]. These retinal diseases modify certain pathways by inducing inflammation and vascular changes, for example [8]. For separating these lesions, a variety of conventional image processing and machine learning (ML) approaches have been

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suggested in the literature [9]. Using kernel functions to convert the input features into hyperplanes, Support Vector Machines (SVM) are a crucial technology that aids in the quick and accurate separation of various classes [10].

Convolutional Neural Networks (CNN) have recently benefited the field of image processing [11]. The integration of the numerous picture characteristics and classifiers in CNN leads to an end-to-end system needing little preparation. The number of layers and their depth can have a big impact on how well feature extraction works. Deep learning networks (DL) were discovered to optimize performance. However, when the network's depth increases, numerous issues including degradation and disappearing gradients may be introduced, leading to large training errors. In the literature, many architectural designs have been put out to enhance these networks for picture categorization.

The goal of this work is to create a hybrid deep learning feature-based system that can automatically identify and diagnose Diabetic Retinopathy (DR) using eye fundus pictures. It takes a lot of time and requires professional personnel with extensive knowledge in identifying this eye ailment from medical imaging and other criteria to manually diagnose this medical picture. When qualified medical professionals make the diagnosis, it also becomes a costly one. Additionally, only a certain number of patients may be handled at a time due to human limits. The technique is also vulnerable to human mistake, which can occur often throughout various doctor performed medical diagnosis processes. Therefore, the need of receiving a second opinion is always emphasized for people who have been given a critical medical diagnosis. Due to all of these drawbacks, automating this process would, if it were possible, save costs, decrease diagnostic mistakes, and speed up the operation so that lots of patients might be processed continuously. However, the output of such a system will help these experts so that they do not have to spend as much time processing a patient as they would manually. With this technique, we are not advocating the abolition of the specialized physicians. This work aims to develop a hybrid deep learning feature-based automated system that can automatically identify and diagnose DR using eye fundus pictures. The system will be able to recognize and diagnose based on any new image from the test dataset after being trained on a dataset. The technology will be able to aid clinicians in the accurate identification of this ailment while decreasing human error and expenses, provided that the detection and diagnostic accuracy is high. The technology will also be able to address any issues with the manual diagnosis that were previously noted. The pre-trained CNN models DenseNet [12] and ResNet [13] are used in this study to extract features from the fundus pictures and conduct binary and multiclass classifications of the fundus images.

II. METHODOLOGY

The hybrid strategy based on DenseNet and ResNet architecture based on transfer learning. The images are scaled and normalized during preprocessing to meet the DenseNetNet and ResNet Models' specifications for input images. Both architectures' layers were frozen while the input fundus images were run through these models. We remove the SoftMax layer, which is utilized for classification in these models, and extract features from the fully linked layer at the conclusion of each design. On the input fundus images, each of these models applies the convolution, normalizing, and pooling layers. The ResNet model employs skip connections to prevent deterioration and minimize the training error, whereas DenseNet improves the decreased accuracy brought on by vanishing gradient. The images are fed into the DenseNet and ResNet transfer learning models after the preprocessing stage. Each model will be used to extract a total number of features. The Support Vector Machine, a well-known classifier, will then receive the combined features as input. To assess the performance of the classifiers and compare the outcomes of this study with similarly proposed approaches in the existing literature, metrics like as Precision, Accuracy, Recall, and F-measure will be employed.

A. Dataset

The dataset from the Asia Pacific Tele-Ophthalmology Society (APTOS) for blindness detection contains the fundus images that were used to train the system. On the Kaggle website [14], the data are accessible. The collection includes 3662 fundus images that were gathered from The Aravind Eye Hospital in India. The below fig.2 shows Number of images in each class.

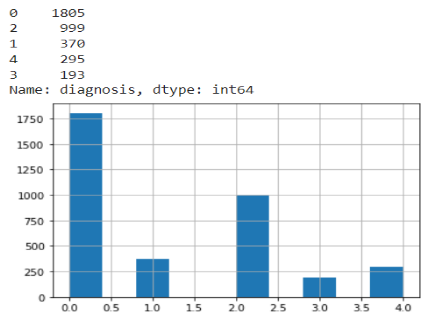

Figure 2. Number of images in each class.

The below fig. 3 shows five levels of DR classification—0 (No DR), 1 (Mild DR), 2 (Moderate DR), 3 (Severe DR),

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and 4 (Proliferative DR)—are used in the labels for the images.

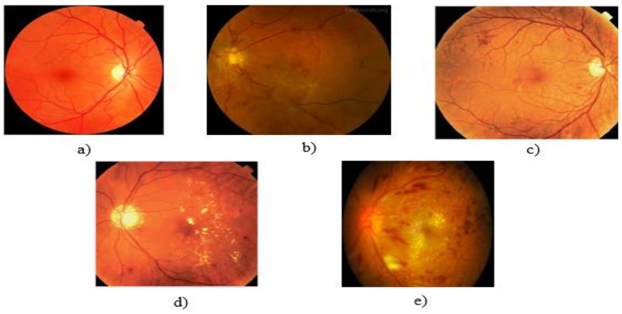

Figure 3. Classified Image Samples. a) No DR., b) Mild DR., c) Moderate DR., d) Severe DR., e) Proliferative DR.

B. Data pre-processing

To create a centered retinal image, a circular crop was used after the unhelpful black portions on the sides of the images were removed. The following equations explain a filtering strategy [15] that was used to improve the clarity of visual biomarkers:

$$X'' = \alpha \times X + \beta \times X' + \gamma \quad (1)$$

$$X' = G(\sigma x)*X \quad (2)$$

G(x) is a 2D Gaussian kernel with a standard deviation of 15 in the x direction, and X is the input data. denotes the convolution procedure. Empirically, the values of 5, -4, and 70 were determined for α, β, and γ. Each picture was then decoded to a 32-bit floating-point representation after being normalized to lie between [0, 1], scaled to (256x256), and compressed.

C. Data augmentation, balancing & analysis

When APTOS statistics were examined, it was found that there was a serious class imbalance, with 49.29%, 10.1%, 27.28%, 5.27%, and 8.05% of the population falling into the normal, mild, moderate, severe, and proliferative DR classes.

In addition, Intuitions were developed by utilizing its projection in lower-dimensional feature space, Principle Component Analysis (PCA) to reduce the data dimensionality to 500- D, and then applying the t-Distributed Stochastic Neighbor Embedding (t-SNE) algorithm to analyses data distribution across various classes.

- One of the simplest classes to identify is Class 0, which creates feature clusters everywhere across the 2-D space.
- Classes (1-4) exhibit severe overlap, which makes it difficult for the algorithm to choose the right hyperplane.
- Based on our knowledge, we artificially grouped the data into only two regions—infected and health—and saw that DL is capable of handling the binary classification issue.

In order to reduce this impact, we employed an Inverse Number of Samples (INS) learning strategy. We applied the modified Categorical Cross-Entropy loss function (CCE). To lessen overfitting and increase the generalizability of the model, random horizontal, vertical, and rotation flipping and rotation were used. Moreover, it was included in our network as a layer to carry out the transformations described during the training phase and was applied utilizing the on-the fly augmentation approach.

D. Architecture

A convolutional basic backbone model and an attention module make up our approach. For the input fundus picture, the backbone network is first employed as a feature extractor, and subsequently features are enhanced using Transfer learning model for better data representation. Then, using Global Average Pooling (GAP) to average each feature map created by the attention module, they are converted to a one-dimensional array before being classified.

The above fig.4 shows the Flow of hybrid feature extraction and classification of fundus images, which use DenseNet and ResNet for better accuracy. Support Vector Machine (SVM) is used to classify the fundus image.

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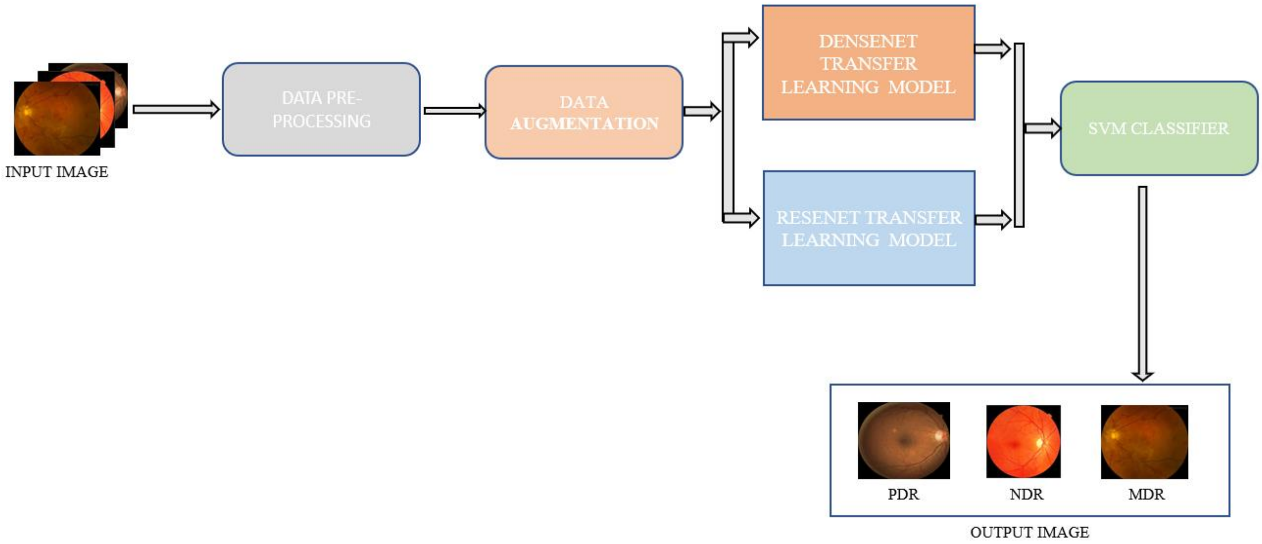

Figure 4. Flow of hybrid feature extraction and classification of fundus image.

1) Transfer learning

An advanced idea in the field of machine learning is transfer learning. With this technique, a model that has previously been trained for a certain job serves as the foundation for a second model. The weights from the pre-trained models are typically employed as the starting point along with deep learning architectures. Tasks involving computer vision and image processing mostly employ this idea. The create model approach and the pre-trained model approach are the two most used methods. In order to classify diabetic retinopathy, the suggested work used two hybrid models, ResNet and DenseNet.

The below fig.5 shows the workflow of Transfer Learning.

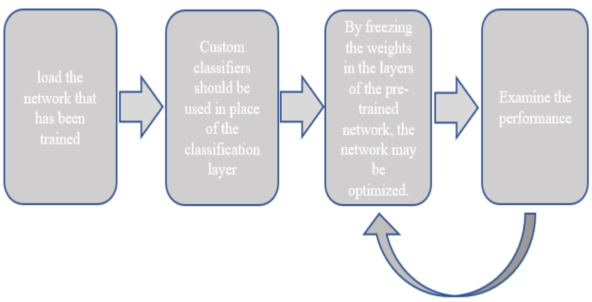

Figure 5. Workflow.

2) Densenet

The goal of DenseNet is to continually deepen deep learning networks. By using short connections between the layers, it is also ensured that the training process is effective. The layers in the model are all interconnected. The network's layers have the greatest possible information flow since all of the levels are interconnected. By verifying that each layer of the neural network received input from every layer before it, the feed-forward mechanism of the network is maintained. Each layer transmits its feature map to the other levels.

3) Resnet

A CNN called a Residual Neural Network (ResNet) uses skip connections to remove particular network layers. The skip connections shorten training time and assist in resolving the CNN's disappearing gradients issue. Between the skipped layers, nonlinear activation functions are used. Also used between the shortcut connections is batch normalization. A weight matrix is used to determine the weights of the jump connections. Later levels of the network apply expansion after understanding the characteristics of the input.

E. Classification of fundus images

Based on the attributes that are collected from the images, machine learning algorithm categories them. The grouping of images with comparable properties is the primary concept behind image categorization. In the classification procedure, linear or nonlinear mixed picture characteristics are employed.

Support Vector Machine (SVM)

Traditional classifiers and supervised machine learning techniques include an SVM. An SVM classifies the input data

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by constructing a hyperplane in a higher dimension space, which is how it functions. The procedure enables the use of a Kernel function to convert the input into hyperplanes, therefore classifying the data into different groups. SVM maximizes the margins between the hyperplane classes while minimizing structural error throughout the classification process. e.g., the Gaussian kernel.

III. Experimental Results

After integrating stage 1-4 images into a single class, i.e., DR, in binary classification, the data are no longer affected by the imbalance problem. We reduce the number of classes for multiclass classification from five to three, namely NDR (stage 0), MDR (stage 1-2), and PDR (stage 3–4). We choose the fewest number of photographs from each of the three classes and then randomly choose a similar number of images from the other classes. With this approach, we get the fewest images—488—in the combination of stage 3–4 labelled class (PDR). Thus, 488 images—488 each from NDR and MDR—are chosen at random from the remaining classes. The CNN models get these images in order to extract the feature vectors. 32 is the specified batch size. The hybrid feature vector, which is distributed to classifier, is created by combining the feature vectors from the various models. Individual transfer learning models that just employ the DenseNet or ResNet feature vector of 1000 features are also sent to the classifiers for further comparison.

The equipment utilized Contains an Intel CPU and 4 GB of RAM in this work. the system's installed graphics processing unit (GPU). The pretrained DenseNet and ResNet architectures based on APTOS image data have their characteristics extracted using MATLAB. In MATLAB, classifier is used to categories input images into binary and multiclass categories.

Accuracy, precision, recall, and f-measure are the assessment metrics that are used to evaluate the system's performance. The percentage of overall predictions that are properly categorized is known as accuracy. What percentage of predictions in a class that are labelled as positive are truly accurate is determined by accuracy. The percentage of actual right labels in the data that the classifier correctly predicted is known as recall. The harmonic mean of recall and accuracy is provided by F-measure.

Table 1. Results of an experimental SVM classifier for binary classification utilizing features taken from the DenseNet Model.

Classifier	Metrics	NDR	DR	Weighted Average
SVM	Accuracy	97.52	97.26	97.39
	Precision	97.30	97.50	97.40
	Recall	97.50	97.30	97.40
	F-Measure	97.40	97.40	97.40

Table 2. Results of an experimental SVM classifier for binary classification utilizing features taken from the ResNet Model.

Classifier	Metrics	NDR	DR	Weighted Average
SVM	Accuracy	97.25	98.08	97.67
	Precision	98.10	97.30	97.70
	Recall	97.30	98.10	97.70
	F-Measure	97.40	97.70	97.70

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Table 3. Results of an experimental SVM classifier for binary classification utilizing combined features from DenseNet and ResNet.

Classifier	Metrics	NDR	DR	Weighted Average
SVM	Accuracy	97.52	98.08	97.80
	Precision	98.10	97.60	97.80
	Recall	97.50	98.10	97.80
	F-Measure	97.80	97.80	97.80

Table 4. Results of a multiclass SVM classifier experiment utilizing features taken from the DenseNet model.

Classifier	Metrics	NDR	MDR	PDR	Weighted Average
SVM	Accuracy	96.00	68.98	74.80	97.80
	Precision	96.60	74.70	68.10	97.80
	Recall	96.00	69.00	74.80	97.80
	F-Measure	96.30	71.70	71.30	97.80

Table 5. Results of a multiclass SVM classifier experiment utilizing features taken from the ResNet model.

Classifier	Metrics	NDR	MDR	PDR	Weighted Average
SVM	Accuracy	96.00	59.49	77.86	77.44
	Precision	90.00	72.90	68.00	77.30
	Recall	96.00	59.50	77.90	77.40
	F-Measure	92.90	65.50	72.60	77.00

Table 6. Results of an experimental SVM classifier for multiclass classification utilizing hybrid features taken from DenseNet and ResNet.

Classifier	Metrics	NDR	MDR	PDR	Weighted Average
SVM	Accuracy	96.66	81.64	90.07	89.29
	Precision	96.70	87.80	83.10	89.40
	Recall	96.70	81.60	90.10	89.30
	F-Measure	96.70	84.60	84.60	89.30

IV. CONCLUSION

In order to extract fundus image characteristics from ResNet and DenseNet models, this work offers a hybrid technique for the early Diabetic Retinopathy identification. These attributes are fed into classifier, which classify DR images from the APTOS dataset using binary and multiclass methods. Combining information from DenseNet and ResNet in multiclass classification helps the system perform better overall by enhancing the MDR and PDR class metrics. The suggested categorization method can help ophthalmologists identify diabetic retinopathy early. The proposed technique has the maximum accuracy for multiclass classification (89.29%) and binary classification (97.8%). The findings also suggest that other machine learning classifiers than ANN can produce quick and extremely accurate results when used after CNN for feature extraction.

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