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An Automated Detection and Multi-stage classification of Diabetic Retinopathy using Convolutional Neural Networks

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***Abstract*— Vision-impairing lesions on the retina are a common consequence of diabetes mellitus known as Diabetic Retinopathy (DR). Failure to diagnose it early can result in blindness. If DR is diagnosed and treated early on, the risk of permanent vision loss can be drastically reduced. Unlike computer-aided diagnosis systems, the time, effort, and expense involved in manually diagnosing DR retina fundus images by ophthalmologists is significant. Medical image analysis and classification are two domains where deep learning has recently become widespread. Convolutional neural networks are the preferred deep learning method when it comes to evaluating medical images. In this study, a method for detecting diabetic retinopathy was presented using DiaNet Model (DNM). The Gabor filter is employed in the retinal Image Pre-processing phase for the purpose of improving the visibility of blood vessels as well as for texture analysis, object recognition, feature extraction, and image compression. In Image Augmentation stage, the dataset's input dimensions are reduced using Principal Component Analysis (PCA). The DNM Model can benefit from a reduction in the number of attributes under certain conditions. A mean classification accuracy of 90.02% was observed, which is significantly higher than state-of-the-art methods.**

Keywords—Diabetic Retinopathy (DR); Convolutional Neural Network (CNN); Deep learning; DiaNet Model (DNM); Principal Component Analysis (PCA)

I. INTRODUCTION

Earlier illness diagnosis increases the likelihood of successful therapy. Lack of insulin leads to high blood glucose levels, the hallmark of diabetes. The number of adults affected by this disease is estimated at 425 million. In addition to renal failure, heart issues, and many other dangerous illnesses, diabetes is also a major contributor to blindness [1]. Diabetic retinopathy (DR), a condition where the blood vessels in the retina enlarge and leak fluid and blood, is brought on by the signs and symptoms of diabetes [2, 3]. If DR progresses to its worst form, it might cause total blindness.

There is a wide range of development in the field of medical imaging techniques, from regions where research is at a purely conceptual stage to sectors where well-developed prototypes are employed in medical research but aren't yet apart of the clinical routine for varied purposes [4].

DR is a potentially fatal retinal disease that affects persons with diabetes. When leaky blood vessels in the eye cause the macula to expand or thicken, they block blood flow to the retina. New blood vessels might form abnormally on the retina at times. In the first stages of diabetic retinopathy, symptoms may not present themselves. It might impair your ability to read or notice distant objects. Changes in one's eyesight, inability to differentiate between different shades of colour, vision distortions like black or empty spots caused by floating particles which results in total blindness.

Among the several forms of computer-assisted medical diagnosis, DL stands out [5]. There are five stages of diabetic retinopathy. If the retina is normal, it is classified as no DR. If the retinal state is abnormal, it is further divided into four categories depending on the extent of the disease: mild DR, moderate DR, severe DR and proliferate DR as shown in Fig.1.

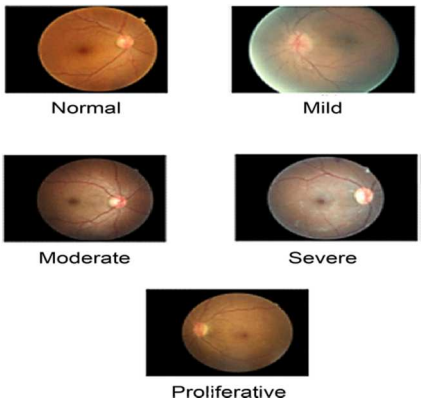

Fig. 1. Phases of Diabetic Retinopathy

Background retinopathy is another name for the mild stage. It suggests that the retina's small blood vessels have extremely minor bulges. Vision issues are probably not present at this point. The retinal blood vessels swell at moderate stage. Its

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swelling may interfere with this crucial aspect of vision. With diabetic retinopathy, 50% of patients will develop moderate DR. There is a higher likelihood that the disease will impact vision once it reaches this stage. The blood vessels are now even more clogged in severe stage. This implies that the retinas receive significantly less blood. As a result, scar tissue develops. The retina may be pulled out from the rear of the eye when the scar tissue shrinks. It may result in the irreversible loss of side and forward vision.

II. Related Work

Today, a sizable portion of the world's population suffers with diabetes. Diabetes diagnoses have sharply increased in India, which has led to an upsurge in a variety of other disorders that are upsetting society. This is why an algorithm is developed in software for early detection of DR in [6]. Potentially useful for timely DR identification that doesn't require a medical professional, this method is cost effective and time-efficient.

Five subtypes of diabetic retinopathy have been identified. They are normal; mild; moderate; severe; proliferate DR. The deadly illness typically requires the processing of a colored fundus picture by specialists. Diabetic retinopathy is difficult to analyze and identify manually due to the high potential for human error. A variety of computer-based methods have been used to identify DR; these methods display the retinal blood vessels but are unable to discern between the early and late stages of the disease. Diabetic retinopathy is categorized into its several phases using an Artificial Neural Network (ANN) in this article [7]. Accuracy and efficiency improved as a result of that.

A unified and objective medical diagnosis is challenging to achieve using the standard manual categorization approach, which necessitates expert knowledge and takes considerable time. Using transfer learning, the author of paper [8] suggests a strategy for detecting diabetic retinopathy. First, get the information from Kaggle's website, and then improve it by amplifying it, inverting it, folding it, and adjusting the contrast. Then, employ a pre-trained model, such as VGG19, InceptionV3, Resnet50, etc. To train each neural network, the ImageNet dataset was utilized. The experimental findings demonstrate that the approach can achieve a generalization ability of 0.60, which is higher than the conventional direct training method.

A computer model based on retinal images and a neural network was developed by the author [9] to make diagnoses of Diabetic Retinopathy (DR). There are two main parts to the computational model: feature extraction and classification. Blood vessel and micro aneurysm identification were used to pull the most relevant characteristics for feature extraction. The CNN was successfully employed to foretell the onset of diabetic retinopathy (DR).

A powerful automated method is proposed in article [10] that can identify and categorize the various stages of DR where STARE, DIARETDB0, and DIARETDB1 are the databases used. Features are being retrieved from the segmented optic disc and retinal nerves using the GLCM (Gray Level Co-occurrence Matrix). For DR stage detection, a Fuzzy classifier and a Convolutional Neural Network(CNN) was employed for classification.

Instead of spending a lot of time manually determining whether or not a patient has diabetes, ophthalmologists are seeking for faster and more efficient ways to make that determination. Therefore, ocular analysis can serve as a portal for the immediate diagnosis of diabetic retinopathy (DR). The author [11] sought to provide a method by which it can be quickly and easily determined whether a person has diabetes or not.

With the aid of publicly accessible datasets, a number of Convolutional Neural Networks (CNN) have been developed to identify the existence of DR. To identify inter-class and intra-class differences from the basic picture data, the suggested method makes use of deep networks and principal component analysis (PCA). With the use of pretrained deep learning architectures, a multi-stream network is created to serve as the main feature extractors. In order to further increase classification accuracy, an ensemble machine learning classifier is created utilizing the AdaBoost and random forest methods[12].

By methodically analyzing benchmark datasets, a clinical dataset, a 5-class classification scheme, and a binary classification scheme in addition to benchmark datasets, significant results for 9 BNNs is reported. Additionally, a link between the classifier risk and the entropy-based uncertainty measure is established. The suggested method [13] can be used to categorize diabetic retinopathy based on clinical data with a reasonable amount of uncertainty, however suitable uncertainty measures are required to maximize the intended performance measure.

A novel approach of stacking generalization of convolution neural networks is developed to build a deep learning based computer-aided diagnostic system (CNNThree custom CNN model weights are fed on top of a single meta-learner classifier to deliver greater metrics of evaluation and accurate prediction outcomes[14].

III. Methodology

The proposed automated detection and multi stage classification of Diabetic Retinopathy starting from the image acquisition and followed by pre-processing, augmentation and categorization of the severity level is depicted in Fig. 2.

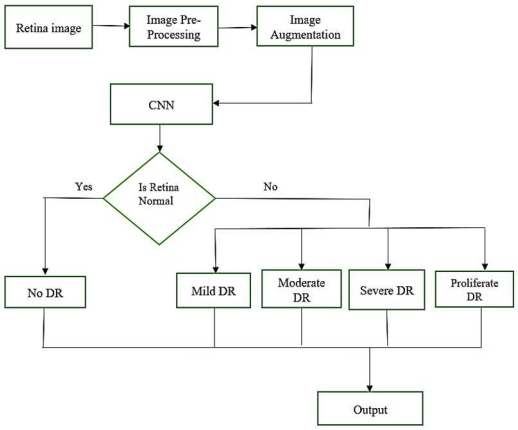

Fig. 2. Block diagram of Diabetic Retinopathy Detection

The pre-processing stage receives the retinal image as input. In pre-processing stage the blood vessels in the retina are segmented and their quality is increased using Gabor filter, the data undergoes augmentation technique which increases the number of datasets and their dimensionality is reduced. The CNN is employed in order to grade the disease's severity.

A. APTOS Dataset

The datasets were collected from APTOS dataset was publicly available in Kaggle datasets. It comprises retinal images from each of the five DR phases. This dataset includes 5590 retinal images, out of which there are 3662 Train images and 1928 Test images. The Fig. 3 shows the retinal images present in APTOS dataset.

Fig. 3. Input datasets from APTOS

B. EYEPACS Dataset

To further refine our models, we utilized pre-existing retinal pictures from the EyePACS dataset. Over 80,000 retinal pictures were included in the EyePACS dataset, each labelled as belonging to one of five severity levels of DR. In which 24611 images are Train images where 18000 images labled as Tlevel0 (no DR), 1713 Tlevel1 (mild DR), 3782 Tlevel2 (moderate DR), 618 Tlevel3 (severe DR), 498 Tlevel4 (proliferate DR). The Fig. 4 shows the retinal images present in EyePACS dataset.

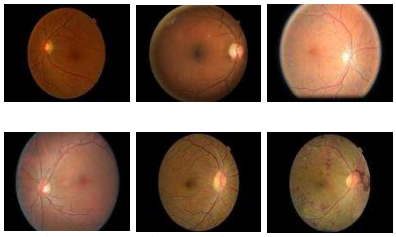

Fig. 4. Input datasets from EyePACS

C. Data Preprocessing

Images require image preprocessing before being used for model training and inference. Preprocessing is done to shorten model training time and speed up model inference. The Gabor filter is utilized in this work to highlight the blood arteries. One systematic technique for automatically separating retinal blood vessels is the Gabor filter. and it is a linear filter used for texture analysis, which implies that it examines whether any localized region near the point or region of analysis contains any specific frequency content in the image in any particular directions. It includes object recognition, feature extraction, and image compression.

$$\sigma_x = k \tag{1}$$

$$\sigma_y = \frac{\sigma_x}{\gamma} \tag{2}$$

$$x_\theta = x\,cos\theta + y\,sin\theta \tag{3}$$

$$y_\theta = -x\,sin\theta + y\,cos\theta \tag{4}$$

Gabor filter kernel:

$$g_\theta(x,y) = \exp\left\{-\frac{1}{2}\left(\frac{x^2{}_\theta}{\sigma_x} + \frac{(yy_\theta)^2}{\sigma_y}\right)\right\}\cos(2\pi\frac{x_\theta}{\lambda} + \Psi) \tag{5}$$

where

Bandwidth of the Gabor filter, $\sigma_x = 19.9$

Wavelength of this filter, $\lambda = 9.8$

Spatial aspect ratio, $\gamma = 6.08$

D. Data Augmentation

It is not possible to train a convolutional neural network with limited amount of datasets. As a result, a data augmentation method like Principal Component Analysis(PCA) is used to add features to the original datasets, including rotation, horizontal flipping, width shifting, height shifting, and zooming. Principal component analysis is an unsupervised learning technique for decreasing the dimensionality of data.

IV. Implementation Of Densenet-169 And Dianet Models

A. Densenet-169

A popular architecture for DL classification problems is DenseNet-169, one of the 169-layer DenseNet family topologies. It has a much lower amount of trainable parameters in comparison to other DenseNet topologies with fewer layers. As a family of very dependable DL designs, DenseNet-169 a very few trainable parameters, and promote feature reuse. The architecture of DenseNet-169 is represented in the Fig.5.

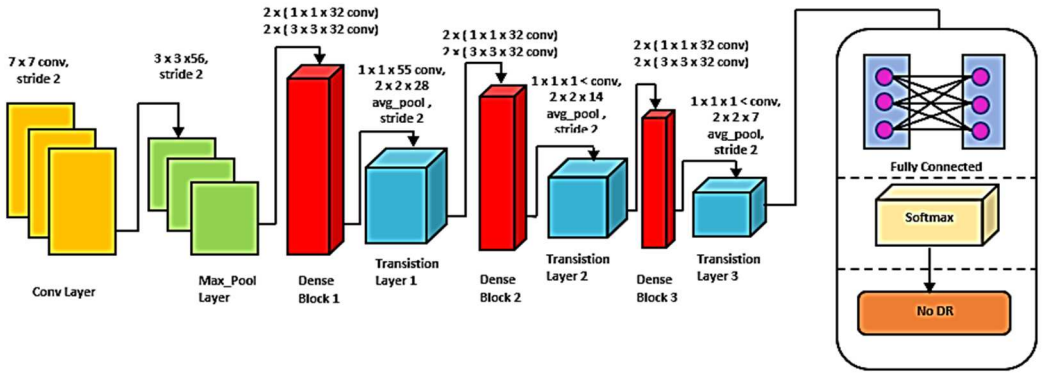

Fig. 5. Architecture of DenseNet-169

Convolutional layers followed by Maxpool layers, Transition layers, Dense layers (fully connected layers) are involved in the architecture. The top layer of the model employs SoftMax activation, whereas the remaining layers of the architecture use ReLU activation. The convolutional layers bring out the properties of the image while the maxpool layers minimize the dimensionality of their inputs.

B. Dianet

The DenseNet-121 backbone serves as the foundation for DiaNet's proposed design, which also includes a pair of pooling layers followed by three composite layers, each of which essentially comprises of batch normalisation (BN), dropout (Dr), linear (Lin), and a ReLU activation layer.

One neuron with the expected label (diabetic/non-diabetic) is present in the final layer. The DiaNet model is able to automatically extract features from input, leading to more precise classification performance. The Fig. 6. Represents the DiaNet's architecture.

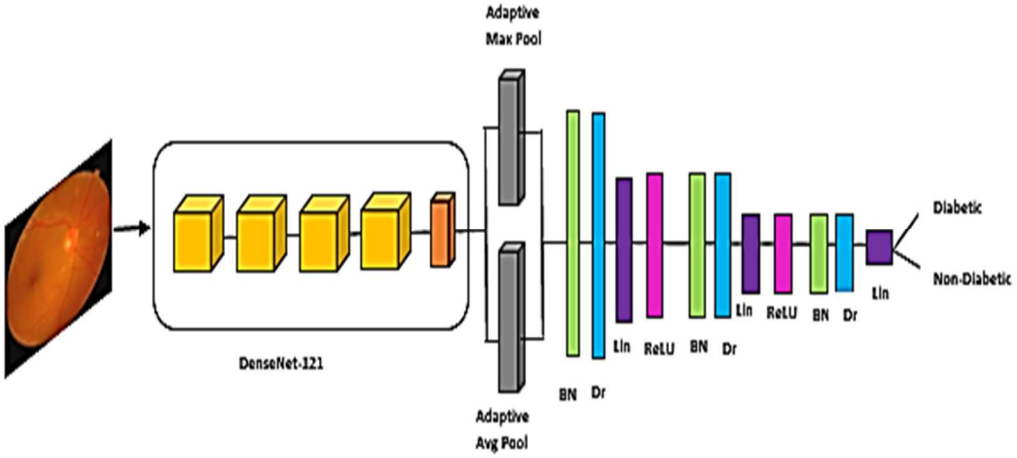

Fig. 6. Architecture of DiaNet

TABLE I. LAYERED ARCHITECTURE OF DENSENET-169

Layers	Output Size	DenseNet 169
Convolution	112×112	7×7 conv, stride 2
Pooling	56×56	3×3 max pool, stride 2
Dense Block (1)	56×56	$\begin{bmatrix} 1\times1 & conv \\ 3\times3 & conv \end{bmatrix} \times 6$
Transition Layer (1)	56×56	1×1 conv
	28×28	2×2 average pool, stride 2
Dense Block (2)	28×28	$\begin{bmatrix} 1\times1 & conv \\ 3\times3 & conv \end{bmatrix} \times 12$
Transition Layer (2)	28×28	1×1 conv
	14×14	2×2 average pool, stride 2
Dense Block (3)	14×14	$\begin{bmatrix} 1\times1 & conv \\ 3\times3 & conv \end{bmatrix} \times 32$
Transition Layer (3)	14×14	1×1 conv
	7×7	2×2 average pool, stride 2
Dense Block (4)	7×7	$\begin{bmatrix} 1\times1 & conv \\ 3\times3 & conv \end{bmatrix} \times 32$
Classification Layer	1000	1000D fully-connected, softmax

TABLE II. LAYERED ARCHITECTURE OF DIANET

Layer Name	Output Size	Number of Parameters
AdaptiveMaxPool2D	[1024, 1, 1]	0
AdaptiveAvgPool2D	[1024, 1, 1]	0
Flatten + Concat	[2048]	0
BatchNorm1D	[2048]	4096
Dropout	[2048]	0
Linear	[512]	1,049,088
ReLU	[512]	0
BatchNorm1D	[512]	1024
Dropout	[512]	0
Linear	[256]	131,328
ReLU	[256]	0
batchNorm1D	[256]	512
Dropout	[256]	0
Linear	[2]	512

Table I shows the layered architecture of DenseNet 169 and the Table II shows the details about the layers that were added to DiaNet architecture at the end of Densenet-121 block.

V. Results And Discussion

This study's primary objective is to develop an algorithm for DR monitoring and to decrease human error in retinal fundus picturing by enhancing computerized detection techniques. The two datasets are used to train the model, APTOS and EyePACS with 80% train dataset and 20% test dataset consisting images comprising all stages of Diabetic Retinopathy. The dataset description is provided in Table1. The images are preprocessed using Gabor filter and segmenting the retina's blood veins makes it easier to detect DR accurately. Then the images undergo augmentation using Principal Component Analysis which increases the number of datasets. The Table III represents the retinal images used in each stage of DR detection. Finally the accuracy is obtained by using two models. First the model is evaluated using DenseNet-169 model. The algorithm was trained for 50 epochs achieved an accuracy of 87.95% as shown in Fig.7. The Loss of DenseNet-169 was shown in Fig. 8.

TABLE III. Image Dataset

Name of the Class	Stages	Count of images
0	Healthy	2184
1	Mild DR	961
2	Moderate DR	1726
3	Severe DR	453
4	Proliferate DR	308

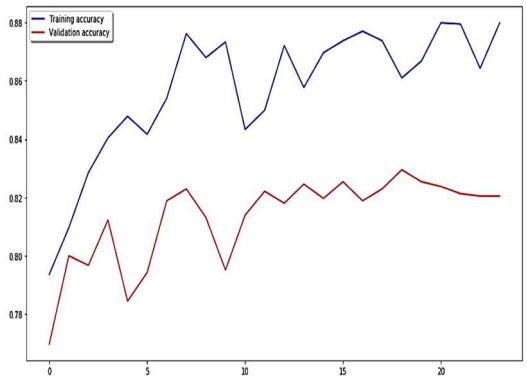

Fig. 7. Accuracy of DenseNet-169

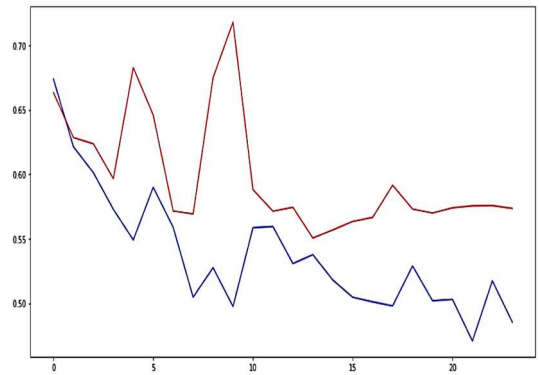

Fig. 8. Loss of DenseNet-169

Similarly, the model is also evaluated using DiaNet which was trained for 56 epochs and achieved an accuracy of 90.02 % as shown in Fig.9. Whereas Fig. 10. represents the Loss of DiaNet model.

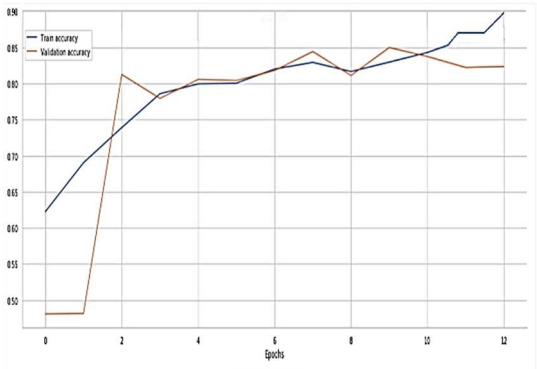

Fig. 9. Accuracy of DiaNet

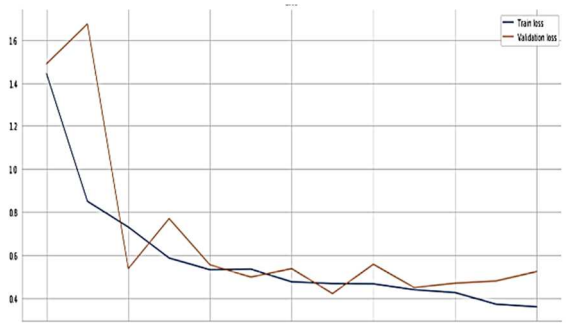

Fig. 10. Loss of DiaNet

TABLE IV. Comparison Of Diverse Models

Model	Accuracy (%)	Loss (%)
DenseNet-169	87.95	47.07
DiaNet	90.02	35.12

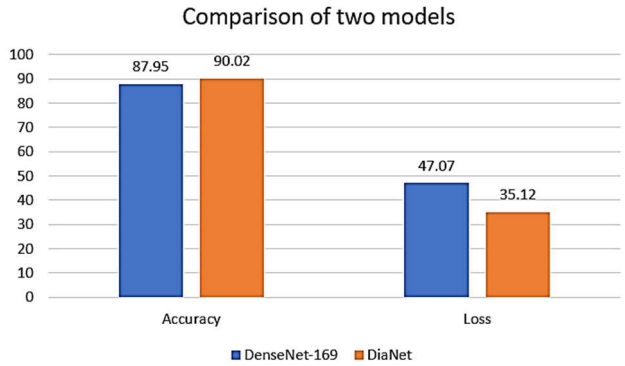

Fig. 11. Comparison of diverse models

The results of the evaluated models are shown in Table IV and the comparison graph of two models are depicted in Fig. 11. From the obtained results, it can be concluded that DiaNet model has achieved highest accuracy when compared to DenseNet-169 model which proves that the DiaNet algorithm detects and classifies the stages of Diabetic Retinopathy more accurately and efficiently when compared to other models.

VI. Conclusion

It is estimated that 425 million persons throughout the world have diabetes, a disorder characterized by elevated blood glucose levels due to an insufficient production of the hormone insulin. Retinopathy is more common among diabetics. Damage to the retinal blood vessels has been linked to hyperglycemia (high blood sugar). As a diabetic eye consequence, diabetic retinopathy causes the retinal blood vessels to enlarge and leak blood. When untreated, it can cause loss of sight in one or both eyes. The proposed method DNM, which detect and classify Diabetic Retinopathy in early stage with accuracy ratio as 90.02% when compared with DenseNet-169. In future, it is possible to enhance the work by utilizing several ensembled algorithms to boost efficiency and aid in DR detection with more accuracy.

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