Fusion-Based CNN Approach for Diabetic Retinopathy Detection from Fundus Images

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Abstract. Diabetic Retinopathy is a state that causes vision impairment in diabetics. Usually, it is brought on by elevated blood sugar, which damages in the eyes and might cause blindness. Blindness may result from a delayed diagnosis. The chance of permanent loss of vision can be considerably reduced aside receiving primal diagnosis and care for DR. The time, effort, and cost associated with ophthalmologists manually diagnosing DR retina fundus photographs are significant when compared to computer-aided diagnosis procedures. Deep learning is becoming widely used in two domains: medical image analysis and categorization. Convolutional neural systems are the suggested deep learning algorithms for evaluating medical pictures. This research proposed a new method for detecting diabetic retinopathy (DR) using the Dia Net Model (DNM), a CNN model that concatenates features extracted from Resnet50 and Inceptionv3 to detect DR. The Gabor filter is utilized for feature extraction, texture analysis, object recognition, image compression, and blood vessel visibility enhancement during the retinal image pre-processing step. An openly accessible dataset of fundus photos is used to assess the suggested model. Compared to the most advanced techniques. The experimental findings show that the proposed CNN model and DiaNet model obtain greater accuracy, sensitivity, specificity, precision, and f1 score.

Keywords: Diabetic Retinopathy, concatenates, DiaNet model, Resnet50, Inceptionv3, CNN.

1 Introduction

A retinal vascular disease known as diabetic retinopathy manifests in individuals with diabetes. It is anticipated that the number of DR patients will double. One important determinant in the formation of retinopathy is the duration of diabetes; a lengthening of diabetes will raise the chance of developing. Additionally, it has been

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observed diabetic forbearing are frequently ignorant about the potential for DR, which delays diagnosis and treatment [1].

Digital color fundus images must be analyzed by qualified clinical professionals, which takes time and is a requirement for manual identification of DR. On the other hand, patients may not receive the necessary follow-up or information due to the delayed outcomes [2]. Until date, ophthalmologists have performed manual testing for diabetic retinopathy. Macular edema and vision loss are the results of diabetic retinopathy that is not proliferative (NPDR), which is distinguished by retinal swelling and small blood vessel leaking. Blood vessel closure is one of the other types of non-proliferative diabetic retinopathy (NPDR), macular ischemia, and exudate formation that may impair vision [3].

The most advanced stage of the condition is called proliferative diabetic retinopathy (PDR), during which neovascular growth causes the retina to produce new blood vessels. If there is significant bleeding in the vitreous, it may lead to impaired vision in addition to black floaters. There's a chance these new vessels will bleed. Widespread formation of scar tissue in PDR can result in independent retinal tissue or cause problems with the eyesight. Several methods, including DL-based methods, have been put forth for the automatic to address these issues, fundus images can be used to identify DR. Using InceptionV3 and Resnet50 to extract features from fundus images, we provide a unique DL model for DR detection in this study.

2 Literature Survey

The sparse principal companent analysis based unsupervised classisfication approach (SPCAUCM) was first presented in order to identify microaneurysms (MA). The properties of the sparse Principal Component Analysis and the elastic net penalty, can be used to choose effective features. The compilation of training sets for non-micro aneurysms is heavily reliant on data, and the large training sets lead to imbalances in the classes as well as delays in processing. Based on the original classification system, The Early Treatment Diabetic Retinopathy Study increase coordination and communication amongst medical professionals who treat diabetic patients and reach a consensus on the global clinical illness classification systems for diabetic macular edema and DR. A study was carried out before the Epidemiological Research on Diabetic Retinopathy in Wisconsin were promulgated. He initiated the DCNN, or Deep Convolutional Neural Networkto identify DR in pictures of the fundus retinal.The Multiple Scale Amplitu demodulation-frequency-modulation (AM-FM) method proposed away as a means of differentiating between aberrant and normal retinal images. Examined were microaneurysms, normal retinal background, hemorrhage, exudates, and retinal neovascularization vasculature patterns. The immediate frequency magnitude, the relative instant frequency angles of many scales, and the instantaneous amplitude cumulative distribution functions are examples of texture feature vectors. The usage within the medical field of computer-aided diagnosis (CAD) field has increased dramatically in recent years. In the medical field, the use of CAD architecture has grown in necessity and is intended to handle classification challenges [6]. One of the main objectives of CAD is the detection of DR through the analysis of multiple characteristics, including veins, texture, hemorrhages, micro aneurysms (MAs), node points, exudate areas, and hemorrhages, the distinction between infected and normal pictures [4]. The results of using DL models in DR diagnosis have been promising. The CNN model is one such model that was proposed by [14]. DiaretDB1 was used for analysis while Kaggle was used for training. Binary data is classified as either clean or contaminated. Another useful DR diagnostic model is the Inception-v4 (HPTI-v4) hyper parameter tuning model, which was presented [15]. CNN models have been investigated in the field of DR in an attempt to increase automated detection. A CNN model was presented in [16], sending lesions to a global grading network using input from two networks. Three models of neural networks - the feed forward nervous system, the profound neuronal net, were disciplined using a kaggle dataset in a different study [17]. Limitations of current techniques: Time-consuming, Prone to errors, Human error is a possibility when diagnosing diabetic retinopathy manually because of the intricate structure of the eye. In contrast to computer-aided diagnosis systems, it results in misdiagnosis.The detection of non-proliferated diabetic retinopathy, or NPDR, can be made more accurate and efficient with the aid of the Prognosis of Microaneurysm and Early Diagnostic System. (PMNPDR) system, which can efficiently train a deep convolution neural network for fundus picture semantic segmentation . The appearance of brilliant spot and red pathology in pathological retinal pictures can be depicted as smooth steps on the step edges or as transient EXs, while the Gaussian axial curves are displayed by MAs.

3 Proposed Methodology

Strong machine learning techniques like deep learning have been used to medical imaging problems like object recognition, segmentation, and classification. DL algorithms have the ability to learn directly from the input, in contrast to classic CNNs that rely on feature extraction techniques.

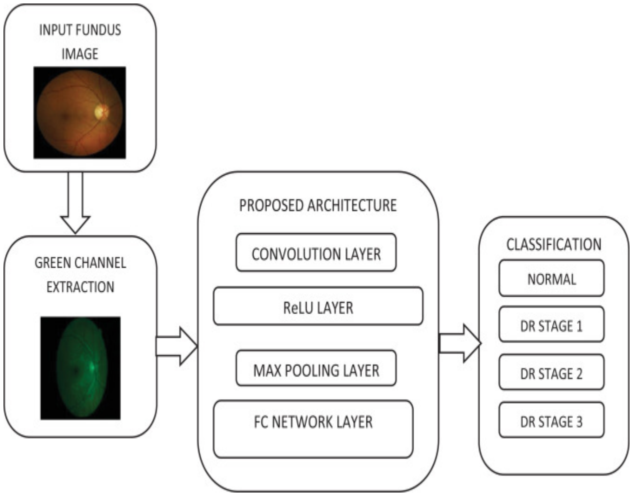

Fig.1. Architecture/Block Diagram of the proposed model

Convolutional Neural Networks (CNNs) are family of deep learning models designed to analyze and assess visual data, such as images and videos. They excel at pattern recognition and feature extraction in particular. Because of their remarkable capacity to grasp complex visual patterns and structures, CNNs have revolutionized image classification, object recognition, and picture segmentation tasks.

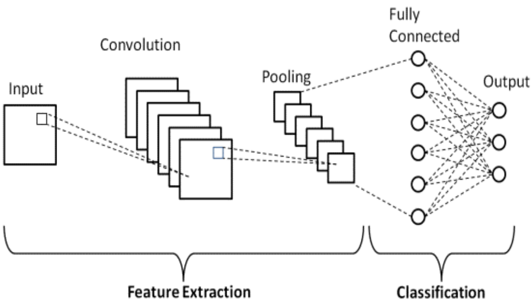

Fig.2. CNN process

- ResNet50: A particular kind of convolution neural network (CNN), ResNet stands for Residual Network. Applications for computer vision often use it as their power source.
- Inceptionv3: A 48-layer convolution neural network is called Inception-v3. On the picture Net dataset, the picture recognition model has demonstrated an accuracy of over 78.1%.
- Concatenates: Feature maps from several layers or scales can be combined using CNN's straightforward but effective concatenation function to increase the expressiveness of the feature representation.
- DiaNet Model: Dense-and-Implicit Attention Network is what DiaNet is short

for. This method uses deep learning to estimate whether a test participant has diabetes based on retinal pictures. In particular, we employed an architecture based on CNN that accepts a retinal image as input. In DiaNet model each neuron only communicates with two synapses from its preceding neurons in neighboring, and fanned the info out to two neurons in the post layer.

Consequently, DL approaches have found application in medical imaging, drug discovery, bioinformatics , finance, and education systems. CNN is the most often utilized method among the several DL algorithms for resolving picture-based medicine issues. The suggested technique uses a hybrid approach with ResNet50 and Inceptionv3 to give an end-to-end mechanism for DR classification.

The DR images were subjected to characteristic activity using the model ResNet50. The supply-forward model known as the residual block, which has link permits insertion of additional component generation of fresh results, was first presented by the ResNet50 model. This method improves the model's performance without appreciably raising its complexity. Resnet50 was chosen for DR detection since it produced the best accuracy of all the DL models taken into consideration.

The GoogleLeNet architecture's InceptionV3 mmodel is the one that is most frequently utilised in the field of medical imaging. It's often applied in the classification process. It is commonly known that the InceptionV3 model may combine filters of various sizes to produce a unique filter, hence reducing the computational cost and the number of trainable parameters.

EVALUATION METRICS

Evaluating the effectiveness of models for machine learning are goal assessment metrics. Performance evaluation metrics utilized in this study are briefly described below.

Accuracy measures are used to assess the proposed model's overall efficacy in identifying the different DR classes.
Mathematically it is presented as:

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

Precision is used to gauge a machine learning model's ability to forecast successful cases with accuracy. Illustrates state between genuine affirmation estimations and the total of incorrectly positive true positive estimates. In mathematics, precision can be expressed as follows:

$$Precision = \frac{TP}{(TP + FP)}$$

Sensitivity represents the total factual positive cases that were accurately classified. The following is the arithmetic formula for sensitivity:

$$Sensitivity = \frac{TP}{(TP + FN)}$$

The sensitivity of a model in medical diagnosis determines how well it can identify individuals who have a condition.

The ability to correctly classify true counter cases is known as specificity, and it is measured proportion of true negatives to the sum of false positives and true negatives in the samples. Real negative rate and selectivity are some other names for it. One way to mathematically express specificity is as:

$$Specificity = \frac{TP}{(TN + FP)}$$

The following are the steps that this study involved.

a) This effort consequently yielded a novel identification model that combines BNs and K-means. To demonstrate the efficacy and optimality of the methodology, three comparison models were developed.
b) The following steps make up the organization of this investigation. The first portion covers data collecting, processing, filtering, and changeable setup relevant to traffic events. Subsequently, BNs, ID3, logistic, and SVM algorithms are integrated with an intensify K-means clustering approach to construct a model for identifying accident hotspots. Third, using the receiver operating characteristic curve (ROC) and additional evaluation signals, the correctness of four models is assessed.

4 Experiments and Results

Clinical testing is typically used to detect the existence of substantial neo biological process and pre-retinal or vitreous hemorrhages. This study uses a publicly available open source dataset.[33]. Each patient's left and right eyes' high-resolution retinal pictures make up 44,119 total images in the dataset.

The pre-process step is crucial to raising the caliber of retinal images since it eliminates noise. The pre-processing methods used in the suggested method are listed below in brief and are intended to maximize image quality.

TABLE 1. Distribution of images according to the presence of DR.

Category	No. of Images	Labels
No DR	25,806	0
Mild	2,440	1
Moderate	5,291	2
Severe	5,291	3
PDR	5,291	4

An output image with a uniform distribution of intensity values is produced by the technique known as histogram equalization. The mathematical statement for histogram leveling is as follows:

$$Specificity = \frac{Pixels\ with\ intensity\ N}{Total\ Pixels}$$

The histogram equalized image is defined by:

$$g_{i\,j} = floor(L - I)\sum_{n=0}^{f_{i\,j}} P_n$$

where floor () reduces to the nearest whole number.

Algorithm 1: Lesions Detection Algorithm

Input: a,b,x,y
Output:G, J(Y;X)
For (a=0)
$L(y,x) = -\exp\left(-\frac{y^2}{2\rho}\right)$
For (b=0)
$T(y,x) = \frac{1}{\rho\sqrt{2\pi}}\left(\frac{y^2-\rho^2}{\rho^4}\right)\exp\left(\frac{y^2}{2\rho^2}\right)$
for (T=1)
$J(Y;X)_{AL} = G(Y)_{AL} + G(X)_{AL} - G(Y,X)_{AL}$
If (t=0)

4.1 Concentration Of Intensity

The image histogram inside the region of interest is expanded to include the whole accessible intensity array via intensity normalisation. Normalization is necessary for neural network training on both identification and generation tasks [20] . The following formula is frequently used to normalize the intensities in each volume.

$$X_{norm} = (I - Min)\frac{Max' - Min'}{Max - Min} + Min'$$

$$X_{norm} = Max' - Min' \frac{1}{1 + exp\, exp\, (\frac{x - \beta}{\sigma})} + Min'$$

The photos are shown in Figure below following the application of intensity normalization.

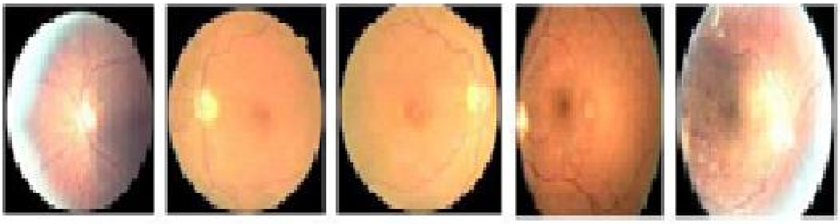

Fig 3: Fundus images from dataset after intensity normalization.

4.2 Outcomes Prior To Data Augmentation

Using the OCT fundus picture dataset and the best model configuration, results were achieved. Because the dataset's image sizes varied, To feed the photographs into DL models, the pre-processing approach entailed scaling them to 256 × 256 pixels, a important initial step in any data-driven investigation.

Table 2 shows the comparison of the model's output.

Result of InceptionV3 model on all the classes of DR.

Model	Class	Label	Accuracy
InceptionV3	No DR	0	90.20
	Mild	1	88.53
	Moderate	2	85.56
	Severe	3	87.41
	PDR	4	83.82
ResNet50	No DR	0	92.32
	Mild	1	89.72
	Moderate	2	90.41
	Severe	3	89.83
	PDR	4	90.92
Proposed IR-CNN Model	No DR	0	97.33
	Mild	1	97.15
	Moderate	2	97.32
	Severe	3	96.07
	PDR	4	96.40

5 Conclusion and Future Work

DR is increasingly identified as a contributing factor to vision loss in working-age persons. For the best results, patients need complete systemic attention, which includes blood pressure and glucose control. Primal sensing treatment of polygenic disorder eye disease's essential to preventing visual loss. The retina's blood container fluid leaking is brought on by long-term diabetes. Determine the stage of DR of research proposes a new CNN network diagnosis of Diabetic retinopathy.

This research study has only just targeted patients with diabetics. Readmission prediction model needs to be generated for other key health conditions and diseases such as Heart disease, kidney disease etc. in Indian Healthcare system. In the future studies, planned and unplanned readmissions needs to be considered. Various other key features in the medical records, like family history (to find hereditary information about the patient), emotional status (depression or other mental issue), socioeconomic status, and lifestyle habits (exercise or yoga), smoking status and season of readmission need to be collected and analyzed.

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