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Diabetic Retinopathy Detection from Retinal Images

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Abstract - **Diabetic Retinopathy (DR) is an eye disease that can occur in people with diabetes causing permanent or temporary blindness, where the blood vessels of retina, a layer in rear interior eye and so called light sensitive part effected by high sugar damages nerves. As I mentioned above, DR can present in various ways; Some people with sick retinas experience blurred vision, while others have difficulty seeing colors or eye floaters. At first, DR might cause no symptoms or only mild vision problems. But it can lead to blindness if left undiagnosed and untreated. This study presents a pipeline for processing and analyzing retinal images. The pipeline consists of three primary steps: (i) pre-processing images, (ii) extracting features, and (iii) classifying the results. The initial step involves pre-processing the image using various modifications to improve its quality and standardize it. Gaussian filtering has been demonstrated to work fairly well in this situation for improving the contrast of the photos. Convolutional Neural Network (CNN) based pre-trained machine learning algorithm is used to speed up the diagnosis of the severity of DR using retinal images of patients. Convolution neural networks (CNNs), among the greatest neural network architectures for image processing applications, have been utilized in the second and third stages.**

***Keywords*-Gaussian filtering,Convolutional Neural Network,Retinalimages,Diabetic retinopathy,hemorrhage,, and exudates.**

I. INTRODUCTION

Diabetes mellitus causes damage to the retina in a medical condition known as diabetic retinopathy, sometimes known as diabetic eye disease. It is the leading cause of blindness in developed countries.Diabetic retinopathy can occur in up to 80% of patients with type 1 and type 2 diabetes who have had the disease for 20 years or longer. At least 90% of fresh instances, the progression to more severe forms of sight-threatening retinopathy and maculopathy could be avoided with appropriate care and eye surveillance. The longer a person has diabetes, the higher their chance of developing diabetic retinopathy. Approximately 3 million Indians aged 40 or older are thought to have VTDR and be at risk of losing their vision.

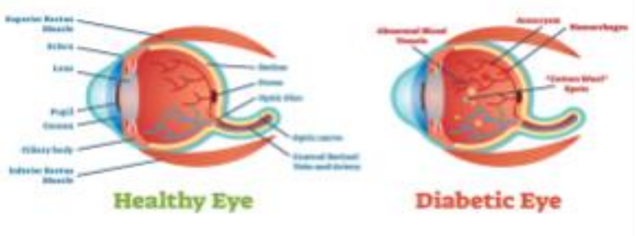

Fig 1 : Image of Healthy Eye & Diabetic Eye [8]

Peripheral vision is lost as a result of damage to the optic nerve. In some cases of diabetic retinopathy, damage to one blood vessel in the retina may also occur.

Convolutional neural networks, an evolution in the field of neural network technology — whose job is to identify those patterns and make it as easy as possible to map each photo into its correct category It is now much easier to train deeper and larger models largely due to the widespread of model-friendly large data-sets set up for online retrieval, advanced models along with aggressive training tricks (batchnorm, RMSprop etc) and enough processing power such as GPU.[/2]

II. SCOPE OF THE PROJECT

The development of a system capable of accurately identifying diabetic retinopathy is the aim of the "Diabetic Retinopathy Detection using Retinal Images" project.Convolutional neural networks (CNN) are used in Diabetic Retinopathy can be found in Retinal scan images. The research seeks to speed up diagnosis and increase the precision of Diabetic Retinopathy detection. The technology will be created to analyze Retinal scan images and detect the existence of Diabetic Retinopathy. The model will be trained to recognize patterns in the

Retina scan images using deep learning technique in general or CNN in particular to show whether there is retinalopathy. "The target of our work is to establish a dataset of retinal scan images that involve diabetic retinopathy cases (both DR and non-DR)," the study explained. cnn models will be with those preprocessed images. The models shall be improved. The new technique of blood-vessel extraction results is relatively better than the matching filter already in place. More importantly, using a nonparametric method algorithm with improved classification accuracy to classify the retinal instances and haemorrhages were also part of our proposed mechanism. This work aims to detect blood vessels, identify hemorrhages, and classify the detected information into three categories: normal, mild nonproliferative diabetic retinopathy (NPDR), and severe NPDR.

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III. LITERATURE REVIEW

K. S. Argade et al. [1]This emphasizes the identification of retinal images by employing advanced image processing and data mining techniques. This makes it simple to distinguish between normal and aberrant retinal scans, which will cut down on the amount of reviews that physicians receive.

R. S. Salvi et al.[2]The paper evaluated the transfer learning using state-of-the-art and scalable CNN architectures for Diabetic Retinopathy (DR) classification. It specifically targets VGG16, ResNet50 V2 and EfficientNet B0 family of models as a baseline.JTextField[scientific,JJ] Performance of the classification is measured by depending on several indicators like True Positive Rate (TPR), False Positive Rate (FPR), Accuracy and all of relevants.

S. Thora et al.[3] The goal of this study's DR detection method is to apply deep learning to automatically identify the problem. Using retinal photos made available to the public by eyePACS on the Kaggle website, the model is trained on a GPU.

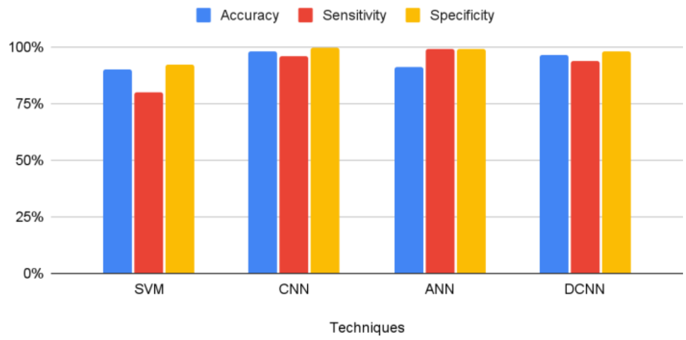
M. Vaisnav, S. Rishi et al.[4] In order to increase accuracy in this segmentation procedure, we employ the debauched vessel segmentation method, which will allow us to remove blood vessels from the fundus images and make processing easier. The precise division of the retinal vessels has been ascertained and put into practice. For blood vessel extraction, an edge enhancement and detection technique are investigated.

C. M. Patil and Y. K. S et al..[5] a. This research proposes three ways to automatically detect glaucoma in humans using fundus database images: The Gray Level Difference Method employs an ANN classifier, the Stochastic Watershed Method uses an SVM classifier, and the Pearson R Correlation Method. Among these, the SVM classifier yields the most accurate results.

Y. S. Boral and S. S. Thorat[6] In order to increase the efficiency, this research suggests an algorithm that combines an enhanced DR detection technique. For DR feature extraction, a deep neural network technique known as Inception v3 is employed. The Inception V3's many picture classification features can be altered by using the transfer learning approach.

S. Burewar et al.[7] This article aims to detect the various stages of Diabetic Retinopathy by automatically diagnosing and classifying high-resolution retinal fundus images into five severity phases. This process utilizes U-Net segmentation with region merging in conjunction with a Convolutional Neural Network (CNN).

Fig 2: SHOWS THE COMPARISON OF SENSITIVITY, SPECIFICITY



Techniques	Accuracy	Sensitivity	Specificity
SVM	90%	80%	92%
CNN	Best	Best	Best
ANN	91%	99.1%	99.1%
DCNN	96.5%	94%	98%

Comparison of different techniques
Table1: Comparison of different techniques[8]

Machine learning techniques that can be applied to classification tasks include SVM, ANN, CNN, and DCNN. SVMs are one of the supervised learning algorithms that may be used for both regression and classification applications. They work by figuring out which hyperplane splits the data into different classes the best. Applications for ANN-type neural networks include supervised and unsupervised learning tasks. They consist of multiple tiers of interconnected nodes with the ability to recognize patterns in data. CNN is one type of neural network that excels in image categorization applications. While pooling layers are used to reduce the dimensionality of the feature maps, convolutional layers are used to extract features from images.

IV. METHODOLOGY

This section provides a detailed description of the proposed technique for detecting exudates in retinal images as shown in fig 5

A. Database Collection

Retinal photos were gathered from the public Kaggle database in order to create the effective database needed to build the An algorithm designed for the automated identification of diabetic retinopathy utilizes a dataset comprising over 4500 retinal images in JPEG format, each with a resolution of 224×224 pixels. These RGB images depict various lesions, including hemorrhages and exudates.

B. Pre-processing

Because of the high level of noise in this data, several preprocessing stages were used to get every image in a format that could be used for training. Cropping, resizing, and getting rid of black photos are all part of preprocessing. To reduce the number of data points and bring the photos into a consistent shape, they are downsized to 224x224 pixels, as illustrated in Fig. 2. A few of the dataset's photographs must be deleted because they are totally blacked out. To accomplish this, take the arithmetic mean of every pixel and compare it to zero. The image is dropped since it is black if the mean is

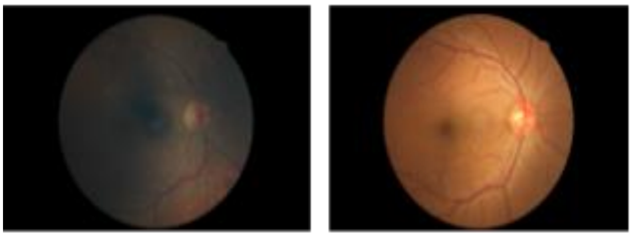


Fig 3. SAMPLE IMAGES OF RETINA(256x256)px

C. Segmentation

Three different approaches were followed to identify the particular objects of interest within an image for picture segmentation. We first adopted the edge detection approach. For the second method, I also got filtered and edge segmented images using eg a threshold. Finally, region based segmentation was performed. To locate edges in an image the magnitude of the first derivative is used to perform edge detection: The second derivative is characterized by two properties:

The second derivative has two important properties: (1) it gives two values for each edge in an image; and (2) you can utilize its zero crossings to locate thick edge centers. On the other hand, thresholding is the simplest technique for segmenting images. It requires converting a grayscale picture to a binary image.

D. Feature Extraction

Following the segmentation stage, candidate regions must be categorized as Hard Exudates (HE) or No Hard Exudates (no HE).To feed a classification algorithm, it is crucial to extract a set of features from each region.One of the most important aspects of a picture is its texture, and a texture feature extraction technique has been presented that combines the gradient histogram with the gray level co occurrence matrix (GLCM). The pixel intensity of a particular image is represented by the HOG (Histogram of Gradient). [9]

E . Convolutional Neural network(CNN)

Convolutional neural networks (CNNs) are a type of feed-forward artificial neural network that utilize convolution operations between layers to classify images. Previously handwritten characteristics can now be learned by the CNN network on its own. CNN is now quicker than conventional algorithms as a result. An input layer, an output layer, and several hidden layers, including activation, pooling, convolution, and fully linked layers, make up every CNN network. Every one of these hidden assignments has a specific duty allocated to it. The CNN's design is determined by the mission or aim assigned to it.(7)

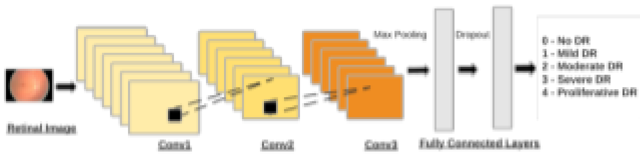


Fig 4 .Convolutional Neural Network[3]

CNNs perform better because of their "feature detector"-like filters, which resemble parts of the human visual system. CNN consists of an input layer, an output layer, and many hidden layers. Examples of hidden layers are activation layers, pooling layers, convolution layers, and fully connected layers. The representational diagram for CNN.(7)

A.Convolution Layer

During each forward pass, theA filter is applied to the input volume by computing the dot product at each position, resulting in a 2-dimensional activation map for that specific filter. The summation of activation maps for each filter across the depth dimension constitutes the total output volume of the convolutional layer. Consequently, each entry in the output volume can be interpreted as the output of a neuron.

B. Pooling

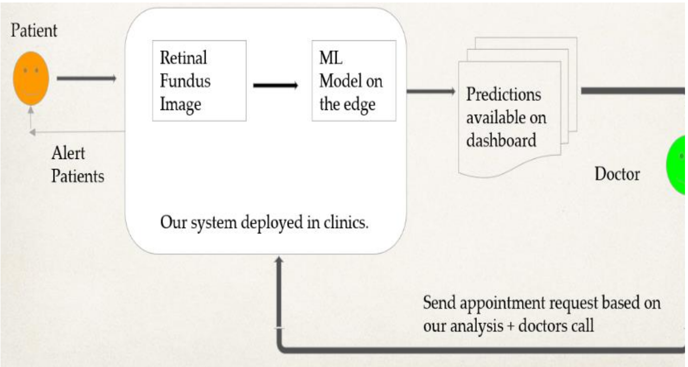
Downsampling is done nonlinearly by pooling layers. The idea is that a feature's precise location is unimportant when considering how it is estimated to relate to other features. The most popular non-linear function for implementing pooling operations is max pooling. The input image is converted into a set of non-overlapping rectangles with maximum outputs.

C.Fully Connected Layer

This is CNN's high-level reasoning layer. Every neuron in a completely connected layer is linked to every activation function found in the layers before it. [7]

D.ReLu Layer

The Rectified Linear Function, or RelLu, is a non-saturating activation function.the Relu function that enhances a network's nonlinear characteristics. The receptive fields of a convolution layer are unaffected by the Relu function.



V. RESULT AND ANALYSIS

In this project all data are tested and evaluated on the stance of the expected technique on the STARE dataset. The dataset consists of 4500 retinal images; the audition was conducted by CNN classifiers. The approaching system was evaluated by the common measurements of sensitivity (Sen.), specificity (Spec), positive predictive value (PPV) and accuracy (Acc).These parameters were computed from the following equations:

Accuracy=(TP+TN)/(TP+TN+FP+FN)

where

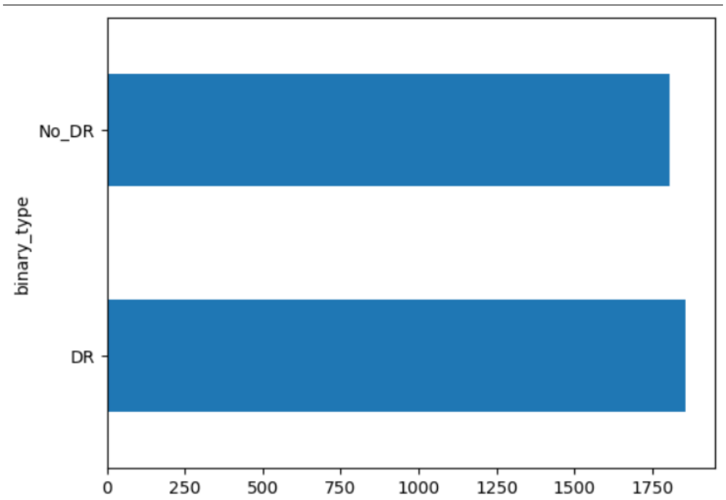
TP (True positive) is a normal image correctly classified by the classifier FN(false negative)is an abnormal image wrongly classified by the classifier. TN (true negative) is a normal image wrongly classified by the classifier. FP(false positive)is an abnormal image correctly classified by the classifier.

The above graph shows the segregation of Non-DR and DR images, illustrating the classification accuracy of the expected technique on the dataset. This segregation highlights the method's ability to distinguish between images with diabetic retinopathy (DR) and those without (Non-DR), indicating its potential efficacy for early diagnosis and screening in clinical settings.

This image is classified under No-DR

This retinal image is classified under DR

These images are the result of the module predicting the Non-DR and DR images, demonstrating the capability of the model to accurately classify retinal images into diabetic retinopathy (DR) and non-diabetic retinopathy (Non-DR) categories. These results reflect the model's proficiency in image analysis and pattern recognition, crucial for effective diagnosis. The clear differentiation shown in the images validates the model's robustness and effectiveness, offering a reliable tool for healthcare professionals to detect and manage diabetic retinopathy at an early stage.



```
loss, acc = model.evaluate_generator(test_batches, verbose=1)
print("Loss: ", loss)
print("Accuracy: ", acc)

<ipython-input-11-b08fd55361be>:1: UserWarning: `Model.evaluate_
  loss, acc = model.evaluate_generator(test_batches, verbose=1)
18/18 [==============================] - 11s 569ms/step - loss: 
Loss:  0.18753491342067719
Accuracy:  0.9381818175315857
```

In the image above, we obtained an accuracy of 93% after 20 epochs of training. This accuracy could be enhanced by expanding the dataset and increasing the number of training epochs. A larger dataset offers the model a greater variety of examples, which can improve its ability to generalize and identify patterns. Moreover, extending the number of epochs provides the model with more opportunities to learn from the data, potentially boosting performance and accuracy. Therefore, by augmenting the dataset and prolonging the training period, we can potentially achieve higher accuracy in our model.

Techniques	**Accuracy**	**Sensitivity**	**Specificity**
SVM	90%	80%	92%
CNN	93.8%	98%	100%
ANN	91%	99.1%	99.1%
DCNN	88%	94%	98%

Comparison of different techniques

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VI. CONCLUSION

We developed a deep learning-based system for the automated detection of Diabetic Retinopathy from Retinal images.The proposed system uses a convolutional neural network (CNN) algorithm to extract features from Retinal images and classify them into two classes,DR and No-DR.The system was developed using a large dataset of annotated Retinal images of patients with Diabetic Retinopathy.Our findings suggest that the proposed system can enhance the accuracy and efficiency of diagnosing Diabetic Retinopathy. It has potential applications in clinical environments to assist ophthalmologists in diagnosing Diabetic Retinopathy, ultimately improving patient outcomes. The proposed system offers a promising approach for the automated detection of Diabetic Retinopathy from retinal images through deep learning techniques. Future research could aim at enhancing the system's interpretability and broadening the dataset to encompass a wider variety of patients and clinical scenarios.

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