Diabetic Retinopathy Using Deep Learning

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Abstract:- Untreated diabetic retinopathy, a complication of uncontrolled diabetes, may lead to total blindness if not addressed promptly. Consequently, in order to avoid the serious complications of diabetic retinopathy, it is crucial to diagnose the condition early and treat it medically. Patients go through a lot of pain and suffering as ophthalmologists manually identify diabetic retinopathy. With the use of an automated method, diabetic retinopathy may be detected more rapidly, allowing for easier follow-up therapy to prevent more eye damage. This paper presents a machine learning strategy for feature extraction including exudates, hemorrhages, and micro aneurysms. The strategy involves a hybrid classifier that integrates support vector machine, k closest neighbour, random forest, logistic regression, and multilayer perceptron networks. To further assist in DR stage image recognition, for instance to detect blood vessels, future research may center on applying object identification techniques based on convolutional neural networks (CNNs).

Keywords:- *Diabetic, Deep learning, Retinopathy.*

I. INTRODUCTION

One of the most dangerous complications of diabetes is diabetic retinopathy, which affects the eyes. Damage to the blood vessels in the retina, a light-sensitive region located toward the back of the eye, causes this condition. Over time, irregularities, leakage, or occlusion in the retina's tiny blood vessels might develop in patients with diabetes.

Diabetic retinopathy may worsen over time, leading to blindness if not addressed. It is one of the most common causes of blindness in individuals who are of working age. Fortunately, diabetic retinopathy may be prevented from causing irreversible vision loss if caught early and treated promptly.

Regular eye tests and examinations are crucial for those with diabetes, since diabetic retinopathy may progress silently in its early stages. Diabetic retinopathy may be diagnosed and treated by ophthalmologists using a variety of imaging modalities, such as dilated eye exams, fluorescent angiography, optical coherence tomography (OCT), and retinal photography.

Once diabetic retinopathy has been discovered, treatment options may include the use of a laser to close any open blood vessels, injections of medicine to decrease inflammation and swelling, or, in more severe instances, surgical intervention. Preserving eyesight, preventing more retinal damage, and controlling blood sugar levels are the goals of therapy for underlying diabetes.

Regular eye exams, along with strict control of blood sugar, blood pressure, and cholesterol, are essential for the prevention and treatment of diabetic retinopathy. To lessen the severity of diabetic retinopathy's effects on eyesight and general eye health, it is crucial to recognize the disease early, treat it appropriately, and actively manage diabetes.

In order to keep their eyes healthy, people with diabetes must carefully collaborate with their healthcare professionals, especially ophthalmologists or optometrists. Protecting one's eyesight and overall quality of life from diabetic retinopathy is possible if one is aware of the dangers and takes the appropriate measures.

II. LITERATURE SURVEY

[Farrikh Alzami, 2019] outlined a method for classifying diabetic retinopathy grades using the MESSIDOR dataset and fractal analysis. As features, their method calculated the fractal dimensions after picture segmentation. They were unable to differentiate between moderate and severe diabetic retinopathy.

[Qomariah 2019] proposed a system that uses support vector machines and concurrent neural networks to automatically classify photos of normal retinas and diabetic retinopathy. Exudates, hemorrhage, and microaneurysms were the features. The author split the suggested system in half, with one half using support vector machines (SVMs) for classification and the other half relying on neural network feature extraction.

[Kumar, 2018] presented a method to enhance the identification of diabetic retinopathy by the extraction of microaneurysm area and number from color fundus pictures sourced from the DIARETDB1 dataset. Green channel extraction, histogram equalization, and morphological processing were used for pre-processing of fundus pictures. Linear support vector machines (SVMs) perform classification and principal component analysis (PCA), morphological processing, contrast limited adaptive histogram equalization (CLAHE), and averaging filtering are used to identify microaneurysms.

[Sangwan, 2015] outlined a method for classifying diabetic retinopathy according to the presence or absence of blood vessels, hemorrhage, and exudates. Before feeding

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them into the neural network, the features are retrieved by picture pre-processing.

Using support vector machine (SVM) training on the supplied data, we may categorize the pictures as either mild, moderate (non-proliferative), or proliferative diabetic retinopathy. When the amount of exudate in the fundus pictures is larger than an optical disc, however, the device will not provide the desired results.

[Morium Akter, 2014] laid forth a method for detecting exudates from color fundus pictures using morphology. The model employs a number of techniques, including: grayscale conversion, thresholding, erosion, dilation, logical AND operation, watershed transformation, and histogram equalization. A variety of diabetic retinopathy exudates are considered in the system's final result.

[Handayani, 2013] created a means of classifying diabetic retinopathy that does not display proliferation by using soft margin support vector machines. The appearance of hard exudates in retinal fundus photographs is used to classify the severity level of non-proliferative diabetic retinopathy. Using mathematical morphology, hard exudates are segmented. But the system does not include microaneurysms or bleeding.

III. METHODOLOGY USED

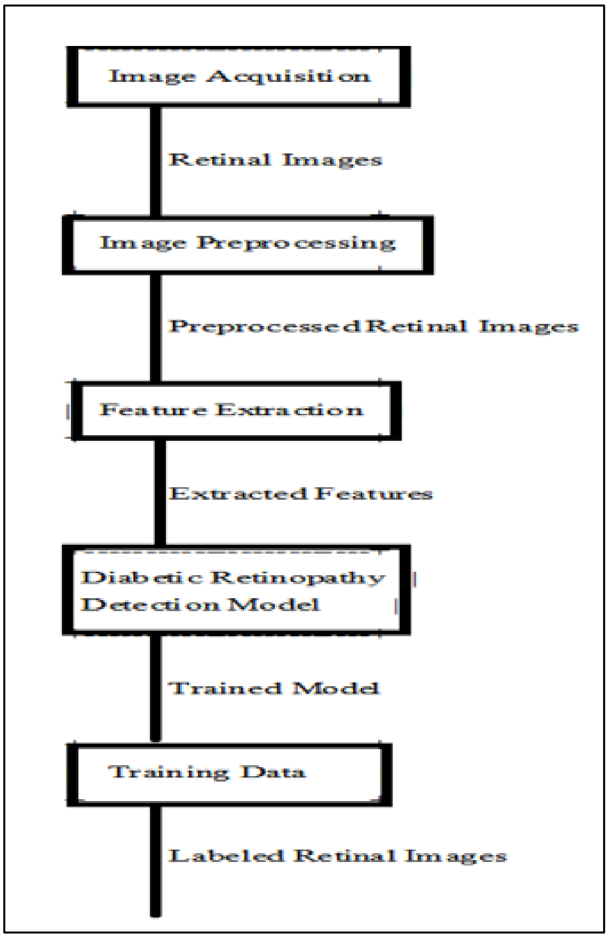

Fig 1: Flowchart

A. Performance Measures

To evaluate the efficacy of DL approaches in classification tasks, a variety of performance metrics have been developed and used. AUC, sensitivity, specificity, and accuracy are the most common DL measures. Specificity is the percentage of normal photographs accurately classified as normal, whereas sensitivity is the percentage of abnormal photos correctly identified [65]. AUC graphs sensitivity and specificity. We define "accuracy" as the percentage of accurately classified photographs. The formulae for each measurement are below.

$$(1)\ \text{Specificity} = TN / (TN\ FP)$$
$$(2)\ \text{Sensitivity} = TP / (TP\ FN)$$
$$(3)\ \text{Accuracy} = TN + TP/(TN + TP + FN + FP)$$

True positive (TP) is the number of illness-classified photographs. False positives (FP) are healthy photos misidentified as unhealthy, whereas true negatives are healthy images misidentified as normal. False negatives are aberrant images mislabeled as normal. The research that informed the present effort and the proportion of performance metrics used.

B. CNN Model

In order to make the retina fundus picture easier to see, we shrank it to a size of 32 × 32 pixels. After feature extraction, the convolutional neural network (CNN) will undergo training until convergence. The accuracy of the DR classification will then be evaluated. Convolution layers enhanced DR classification performance by extracting features for linked tasks based on lesion detection and segmentation.

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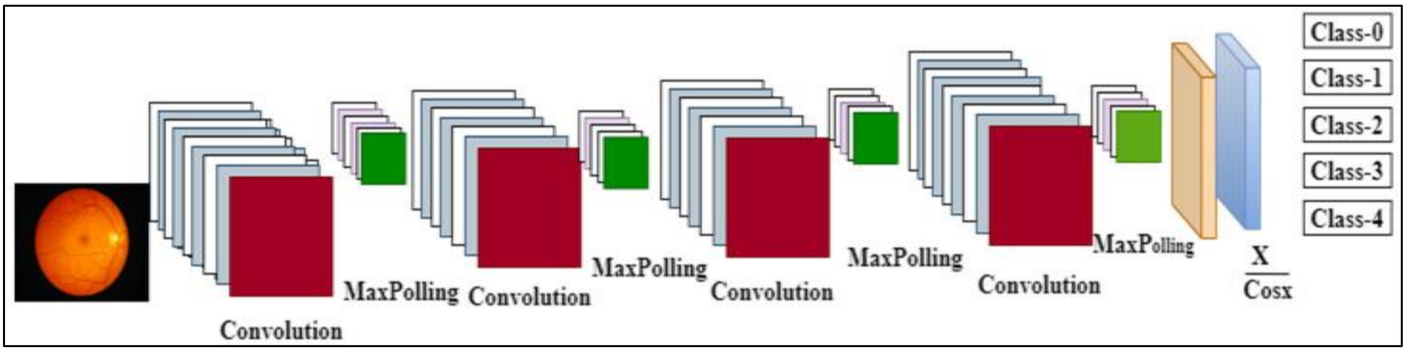

Fig 2: CNN Model

Improving performance during training of the DR fundus picture requires tweaking of hyperparameters. The first layer of the DR is responsible for learning the fundus image's borders, while the second layer is responsible for learning the fundus image's categorization. The max pooling layer minimizes overfitting on dense layers by using the enhanced activation function with a 3 × 3 kernel size and a 1 × 1 stride. During training, each convolutional layer uses backpropagation to create a single-feature map by applying it to various spatial locations.

We trained the weight and bias using the average of the subsampling layer's coefficients. The CNN's suitability for DR classification stems from its cheap computing time during training, which is made possible by its numerous free parameters and the invariant properties of distortion. We used two fully connected layers with enhanced activation functions, four pooling layers, and four convolutions for testing. Each convolution layer made use of a different set of filters with predetermined coefficient values, and the pooling layer always made use of maximum pooling. The convolutional neural network (CNN) is well-suited for DR classification because, by default, it captures implicit and invariant distortion information.

C. Convolution Layer

To feed into the convolution layer, we provide the fundus image matrix and the filter. In order for CNNs to identify pictures, they use receptive fields and shared weights. It is detected by a convolution layer by extracting portions of the fundus picture and activating receptive fields. While CNN feature maps are created in different ways for different applications, they share the same weights and biases that reflect the same features in fundus pictures. The activation map was used to extract characteristics from the fundus pictures.

D. Pooling Layer

The activation map was split in half and the highest value from each half was collected using a max-pooling layer, a nonlinear down-sampling approach. This layer uses the image's produced characteristics to selectively delete data from certain regions. In order to avoid overfitting, the pooling layer minimizes the network's parameters and computation.

➢ *Activation Function*

By include greater sparsity in the hidden units, the suggested enhanced activation function allows for more efficient CNN training when compared to the Sigmoid and other activation functions. We found that it reduced loss more and processed data faster than the traditional activation functions during testing. Equation (5) shows the suggested activation and the first derivative of it.

$$\frac{d}{dx}\left(\frac{x}{\cos x}\right) = \frac{\cos x + x\sin x}{\cos^2 x}$$

➢ *Fully Connected Layer*

Following the pooling and convolution layers, there is a completely linked layer. After the previous pooling layer, all of the neurons are transformed into a one-dimensional layer in this layer. The suggested activation function and the fully linked layer come after many layers. The following are some of the characteristics of the suggested activation function:

- $f(0) = 0$ and $f'(0) = 1$

  $f(x)$ is derivable $\forall x \in R$

  Proof: $f(0^-) = f(0^+) = 0$

  $f'(0^-) = f'(0^+) = 1$

  $f(x)$ is derivable $\forall x \in R$

- When $x > 0$, $f(x) > 0$ and $f'(x) = 1$

  Proof: $\forall x \in R, x\cos x \in [-1,1]$

  when $x > 0$, $f(x) > 0$ and $f'(x) = 1$

$$f(x) = \frac{x}{\cos x}$$

$$= \frac{\cos x + x\sin x}{\cos^2 x}$$

$0 < f(x) < x$ and $f'(x) > 0$

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- As x → +∞, f(x) → 0

  Proof: As x → +∞, f(x) → 0

  As x → +∞, f(x) → 1

In comparison to the Sigmoid and the other activation functions, the suggested enhanced activation function allows for more sparse hidden unit training of the CNN. During training, the enhanced activation function normalizes the input and stays away from saturation circumstances. Both processing time and loss were decreased during testing to a greater extent than with the typical activation functions. By preventing the gradient from becoming zero and normalizing the input during training, the enhanced activation function stays away from saturation circumstances.

IV. SYSTEM IMPLEMENTATION

- Several essential components and procedures are involved in the construction of a system to control diabetic retinopathy. The following is a synopsis of the implementation procedure:
- Health Information Management System (EMR): Start using an electronic medical record system or add features tailored to diabetic retinopathy to an existing one. Information pertaining to diabetic retinopathy screenings, diagnoses, treatments, and follow-up care may be stored, retrieved, and managed more efficiently in this way.
- Imaging and Image Analysis: Establish a system to take pictures of the retina using imaging techniques like OCT or fundus photography. Create algorithms that can automatically examine retinal pictures for microaneurysms, hemorrhages, exudates, and anomalies in the blood vessels—all symptoms of diabetic retinopathy.
- System for Assisting Decisions: Incorporate established criteria and patient-specific characteristics into a decision-support system that aids healthcare practitioners in understanding image analysis findings and formulating treatment recommendations. Individualized treatment programs, severity ratings, and risk evaluations are all within the system's purview.
- Utilize telemedicine skills to provide remote screenings and consultations for diabetic retinopathy. Timely tests and consultations from healthcare experts may now be accessed remotely, even by patients in underprivileged regions or those with restricted mobility.
- Program Integration for Screenings: Work together with public health initiatives and screening programs for diabetic retinopathy to make referrals and data sharing easier. When healthcare providers are integrated, patients can easily share their medical records, at-risk people can be identified quickly, and treatment can be efficiently coordinated.
- Support and Training for Users: Healthcare providers using the diabetic retinopathy management system should be provided with thorough training and ongoing support. Their ability to use the system's capabilities, understand the findings, and make well-informed judgments about patient care is guaranteed by this.
- Safety and Legal Obligation: Maintain the confidentiality of patient information by adhering to all applicable healthcare laws and standards, including HIPAA. Protect sensitive patient data stored in the system by implementing stringent security procedures.
- Ongoing Enhancement and Revised Content: The system's performance should be constantly monitored and evaluated. User input should be collected and used to include enhancements that align with increasing medical recommendations, technical breakthroughs, and user demands. The precision, usability, and general efficacy of the system may be improved with regular upgrades.

A. Screen Shots

Fig 3: Main

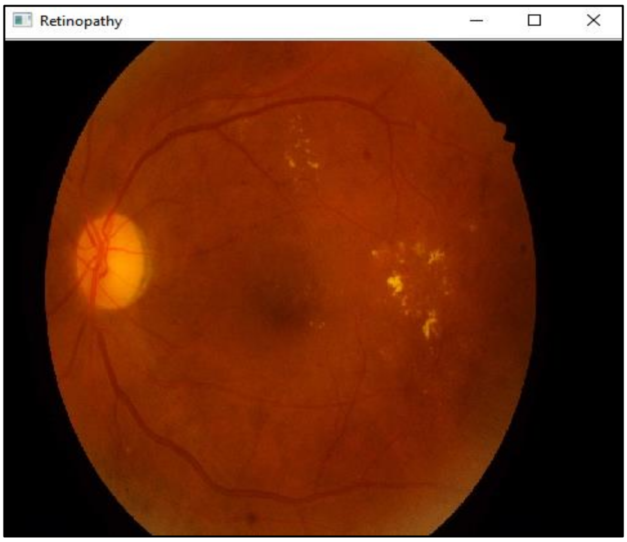

Fig 4: Input Image

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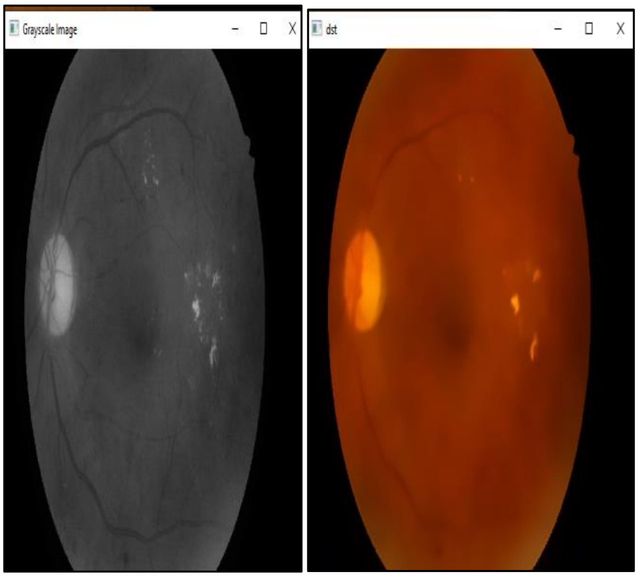

Fig 5: Median Filtering (Preprocessing)

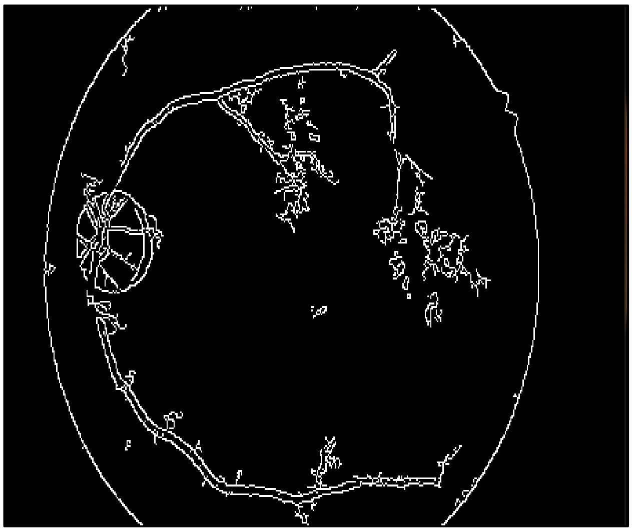
Fig 6: Feature Extraction

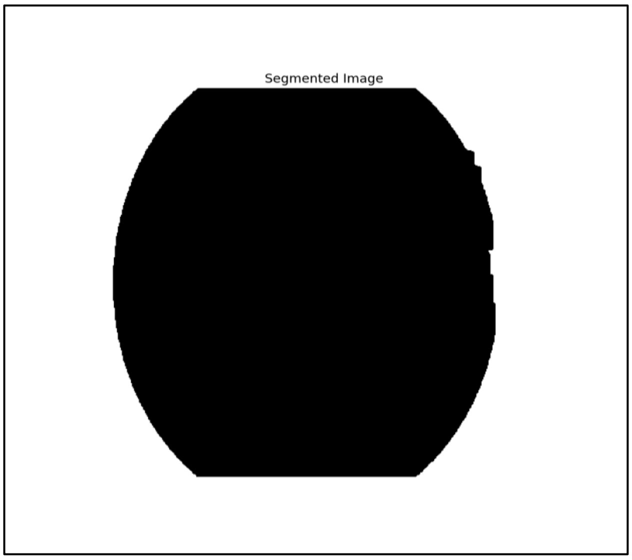

Fig 7: Segmentation

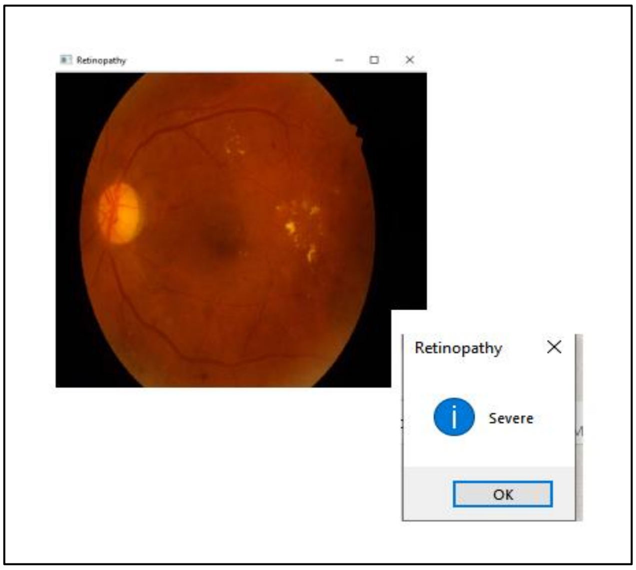

Fig 8: Output

B. Test Results

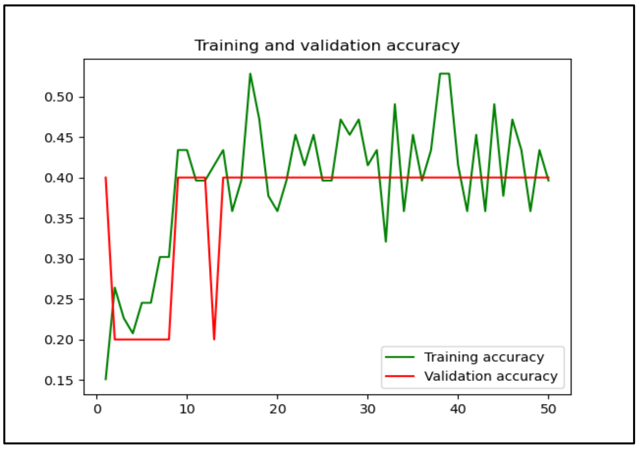

Fig 9: Accuracy Graph

V. CONCLUSION

To sum up, diabetic retinopathy is a major eye problem that, if left untreated, may cause blindness. Early identification, precise diagnosis, and successful treatment of diabetic retinopathy are greatly aided by the deployment of systems for managing this illness.

- These systems allow healthcare providers to screen, diagnose, and monitor diabetic retinopathy effectively by combining electronic medical records, image analysis, decision support systems, and telemedicine capabilities. Accuracy, scalability, security, and usability are key considerations throughout deployment to ensure it meets the demands of healthcare practitioners and patients.
- By allowing for remote consultations, expediting tests, and supporting treatment choices based on evidence, diabetic retinopathy management systems improve patient care. By facilitating communication and collaboration between healthcare practitioners and diabetic retinopathy screening initiatives, these platforms thus contribute to the continuity of treatment.

- For these systems to continue to work and become better, they need regular reviews, upgrades, and strict compliance with security and compliance regulations. Diabetic retinopathy management systems improve patient outcomes, use technology to assist avoid vision loss, and streamline the treatment of this potentially blinding consequence of diabetes.

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