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# Detection of Diabetic Retinopathy using CNN

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**ABSTRACT:** Diabetic retinopathy (DR) is a significant microvascular complexity coming about because of diabetes and keeps on seriously affecting worldwide wellbeing frameworks. The rising circumstance in the creating scene proposes diabetic retinopathy may before long be a significant issue in the clinical world for detection of DR. Diabetic retinopathy or DR is an ailment because of diabetes mellitus that can harm the patient image retina and also cause blood spills. This general condition can also make various indications from gentle vision issues total visual impairment in the event that it isn't convenient treated.

A PC supported determination strategy dependent on profound learning calculations is proposed to automated analyse the referable diabetic retinopathy (RDR) by characterizing shading retinal fundus photos into two evaluations. In this paper, we proposed a calculation that comprises of DR location strategy in combination with convolutional neural network(CNN) with the main aim to improve the precision of the current frameworks. There has been a requirement for extensive and mechanized DR location instruments and techniques. The primary objective is to naturally group the evaluation of nonproliferative diagnosis of diabetic retinopathy at any common retinal image.

**KEYWORDS:** Diabetic Retinopathy (DR), Microvascular Complication, Diabetes Mellitus, Retinal Fundus Images, Blood Spills, Vision Impairment, Deep Learning, Computer-Aided Diagnosis (CAD), Convolutional Neural Network (CNN), Automated Detection, Referable Diabetic Retinopathy (RDR), Nonproliferative Diabetic Retinopathy (NPDR), Image Processing, Machine Learning, Medical Image Classification

## I. INTRODUCTION

Diabetes is a sickness or disease that effects insulin making procedure of the body and prompts demise [1]. Different software analysis frameworks have been created in the course of the most recent decade. Since human specialists for the most part center around some normal sores related with DR, for example, microaneurysms, hemorrhages and hard exudates while assessing retina photos, numerous works focused on automated identify and section these sores or compute some numerical records [3]. CNN calculation gives advantage over others by perceiving designs under outrageous inconstancy, for example, in the event of manually written characters. Diabetic Retinopathy (DR) is the analysis based retinal wound, which brought about by the rise of glucose levels in blood, this can be at last maliciously lead to vision impedence or permanent loss of sight. As it has been indicated by the standards of World Health Organization [4], It has been scientifically evaluated that over 75% of individuals who have diabetes for over 20 years will definitely have some type of DR in the life stages.

Diabetic retinopathy gets symptomatic in a short time later stages. In the primary stage, diabetic patients may not know about having contaminated by the malady [2]. This research paper proposes another PC based software using python language, which has helped determination dependent on the computerized preparing of retinal images so as to help individuals recognizing diabetic retinopathy ahead of time. Numerous specialists have dedicated their push to build up a programmed Computer-Aided Detection (CAD) framework for DR. Different methodologies have been proposed in [3], however DR location in the retinal data images and its exactness are as yet a major test. The constraints are for the most part because of the circular state of the eye, prompting a more splendid locale in the focal point of the retina and dim areas in the outskirts.

## II. LITERATURE REVIEW

Generally, both dichotomy and multiclassification can be used to classify patients with DR (Pires et al., 2017; Araujo et al., 2020; Porwal et al., 2020; Quellec et al., 2021). The dichotomy method can only determine whether a patient suffers from DR, while the multiclassification method can detect the severity of the disease. Here, we introduce several studies of DR detection algorithms applied with these two classification methods.

Binary classification algorithms of DR are widely applied. Qomariah et al. (2019) proposed to use transfer learning in CNN to extract features, based on which the support vector machine (SVM) algorithm was used to classify DR. Chakrabarty (2018) published a deep learning method for the detection of DR. It first converts pictures into gray-scale, second resizes the pictures to 1000\*1000, then scales the pixel values to between 0 and 1, and, finally, inputs the preprocessed picture into CNN to predict the category to which the pictures belong. Chakrabarty and Chatterjee reported an offbeat technique for diabetic retinopathy detection using computer vision (Chakrabarty and Chatterjee, 2019). It first preprocesses pictures, including grayscale conversion, threshold processing, size adjustment, and pixel scaling. Then, the processed images are input into a CNN to extract features, and finally, the features are input into the SVM algorithm for classification. Herliana et al. (2019) applied the particle swarm optimization (PSO) method to select the best DR features, and then the selected features were further classified using the classification method of neural network.

Gautam et al. (2019) used MATLAB based image processing to diagnose DR. First, the image is converted to the specified size and then converted to a grayscale image. Then, adaptive histogram equalization is carried out, and the processed image is distinguished with a threshold value. When the pixel value is greater than the threshold value, this part will be changed to white, otherwise, it will be changed to black. Finally, the number of white pixels is counted. After processing several images, the threshold value of the number of white pixels is determined, which is eventually used for category prediction of images. For the classification of retinopathy and non-retinopathy, Roychowdhury et al. (2014) proposed a computer-aided screening system (DREAM) that combines four machine learning algorithms.

The second approach is to classify DR into multiple categories according to the severity of Kanth et al. (2013) proposed applying “gray scale conversion,” “histogram equalization,” “application of digital filters,” “gradient magnetics segmentation,” and “finally fuzzy c clustering” to extract three features including the sum, average, and sum of exudates of the white pixels with a value of “1” in the binary image, and then used the multi-layer perceptron to classify images.

Zhang et al. (2021) developed an early fundus abnormality screening system (DeepUWF). Firstly, six image pre-processing techniques were used to enhance the image, and then the image was input into the CNN for image classification.

Carrera et al. (2017) first extracted the information of blood vessel, microaneurysm, and hard exudate based on morphology, and then transformed the information into 8 features. Finally, the 8 features were input into the support vector machine for classification.

Wu and Hu (2019) used flip, fold, and contrast adjustment to do upsampling; then the pictures are input to the VGG19, Resnet50, and Inception V3 networks which are trained in the ImageNet data set for transfer learning; and finally, the predicted category of the picture is obtained.

Jayakumari et al. (2020) firstly normalized the Images and then divided the data set into two categories (normal class and disease class including mild, moderate, severe, and proliferative DR) for model training. Finally, according to the model output probability and the set threshold value, the category described in the picture is judged.

In this study, we performed multi classification for the DR dataset. The main contributions of this article are the following two aspects.

- 1.To deal with the extremely unbalanced DR dataset, the total number of images to be upsampled is divided equally among each image, and upsampling is performed by three transformations, including left-right symmetric transformation, up-down symmetric transformation, and random-angle rotation, to achieve the equalization of the dataset. This way of processing can solve the large classification error of the model caused by the unbalance.
- 2.The voting weight of each network model in the ensemble learning is set according to the F1 value validated by the base classifier to improve the detection effect.

### III. PROPOSED METHODOLOGY

#### PROPOSED METHODOLOGY

##### 1. Data Collection and Preprocessing

The first step in detecting Diabetic Retinopathy (DR) using Convolutional Neural Networks (CNN) involves collecting high-quality retinal fundus images. These images are obtained from publicly available datasets like DIARETDB1, DRIVE, STARE, Kaggle’s APTOS, and Messidor. Preprocessing techniques such as image resizing, contrast enhancement, noise reduction, and normalization are applied to improve image quality. Additionally, data augmentation techniques like rotation, flipping, and zooming are used to increase the dataset size and prevent overfitting.

##### 2. Feature Extraction Using CNN

CNNs are used for automated feature extraction, eliminating the need for manual selection. The network consists of multiple convolutional layers, pooling layers, and activation functions to capture essential retinal features such as microaneurysms, hemorrhages, exudates, and blood vessel abnormalities. The extracted features help distinguish between different severity levels of DR, including No DR, Mild, Moderate, Severe, and Proliferative DR.

##### 3. Model Architecture Design

A well-structured CNN architecture is essential for efficient DR detection. A typical architecture includes several convolutional layers followed by ReLU activation, max pooling layers, dropout layers to prevent overfitting, and fully connected layers for classification.

Pretrained deep learning models like VGG16, ResNet, InceptionV3, and EfficientNet are often used for transfer learning to enhance detection accuracy while reducing training time.

##### 4. Classification of Diabetic Retinopathy Stages

The final layer of the CNN model is a softmax classifier that categorizes retinal images into different DR stages. The classification is typically performed using multi-class or binary classification based on the severity levels.

Advanced techniques such as weighted loss functions and class balancing are used to handle data imbalance, ensuring the model does not favor one category over others.

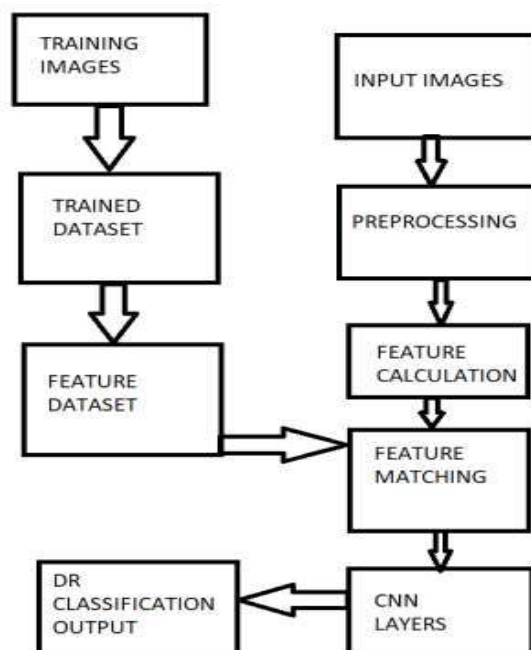


Figure 1: Architecture diagram

### 5. Performance Evaluation and Optimization

To assess the effectiveness of the CNN model, performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC curve are used.

Cross-validation and hyperparameter tuning are applied to optimize the model's learning rate, batch size, and number of layers. Additionally, techniques such as early stopping and dropout regularization help prevent overfitting and enhance model generalization.

### 6. Deployment and Real-Time Implementation

Once the CNN model achieves satisfactory accuracy, it is deployed in real-world applications. The model can be integrated into cloud-based platforms, mobile applications, or hospital management systems for automated DR detection.

By leveraging edge computing and IoT-based solutions, real-time DR screening becomes feasible, reducing the workload on ophthalmologists and enabling early-stage detection for better patient outcomes.

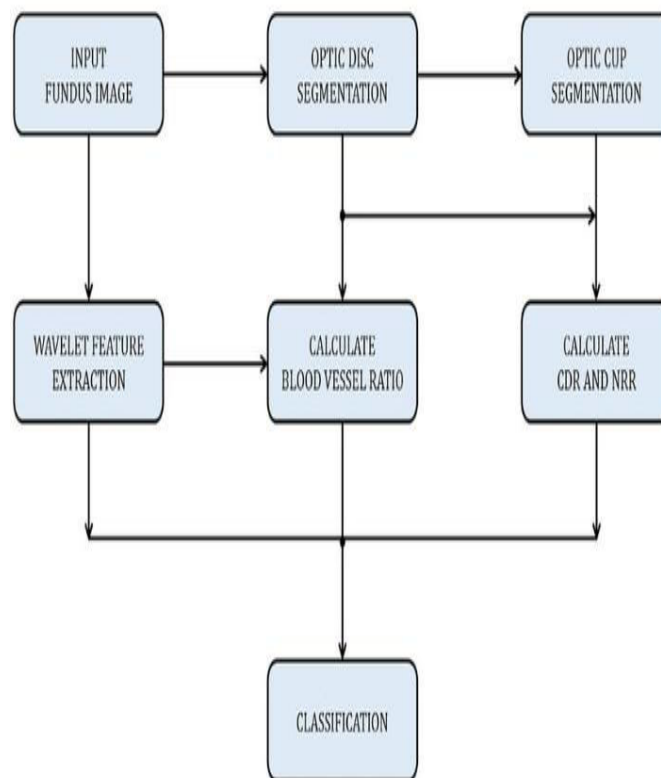


Figure 2: Block diagram

## IV. FINDINGS AND DISCUSSION

### 1. Home Page

The Home Page of the Diabetic Retinopathy Detection System using CNN provides a user-friendly interface for seamless interaction. It features an "Upload" button that allows users to upload retinal fundus images for analysis. Once an image is uploaded, the system preprocesses it and applies the trained Convolutional Neural Network (CNN) model to detect the presence and severity of Diabetic Retinopathy (DR). The "Test" button enables users to run a quick diagnosis, displaying the results with severity classification such as No DR, Mild, Moderate, Severe, or Proliferative DR. The homepage ensures an intuitive and efficient workflow, making early-stage DR detection accessible to both medical professionals and patients.

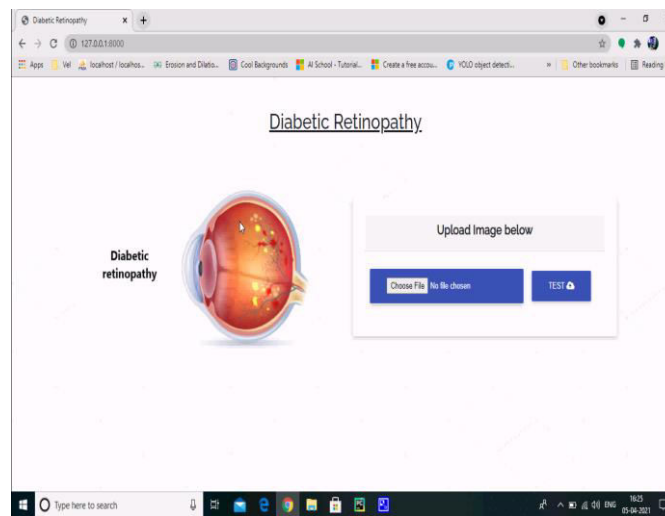


Figure 3: Home Page

## 2. Uploading Image

In the detection of diabetic retinopathy using CNN, uploading an image is the first crucial step in the automated diagnosis process. The system allows users, such as ophthalmologists or patients, to upload retinal fundus images through a web or mobile-based application. Once the image is uploaded, it undergoes preprocessing techniques like grayscale conversion, contrast enhancement, noise reduction, and resizing to ensure uniformity and improve feature extraction. The preprocessed image is then fed into a pretrained or custom-built CNN model, which analyzes the retinal features such as microaneurysms, hemorrhages, and exudates to classify the severity of diabetic retinopathy. This user-friendly interface ensures real-time analysis, providing accurate and quick predictions that assist in early detection and timely medical intervention.

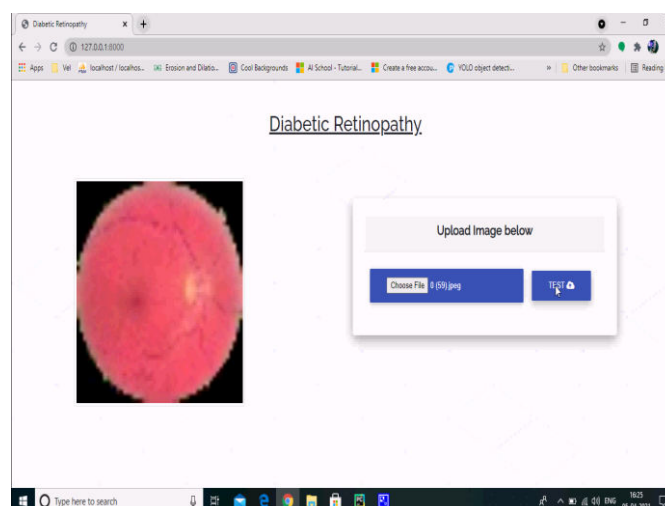


Figure 4: Uploading Image

## 3. Processing of Image

Image processing is a crucial step in the detection of Diabetic Retinopathy (DR) using Convolutional Neural Networks (CNN). It begins with image acquisition, where high-resolution retinal fundus images are collected from medical datasets. These images undergo preprocessing techniques such as grayscale conversion, contrast enhancement, histogram equalization, noise reduction, and normalization to improve clarity and highlight key retinal features. Data augmentation techniques like rotation, flipping, and zooming help in diversifying the dataset and preventing overfitting.

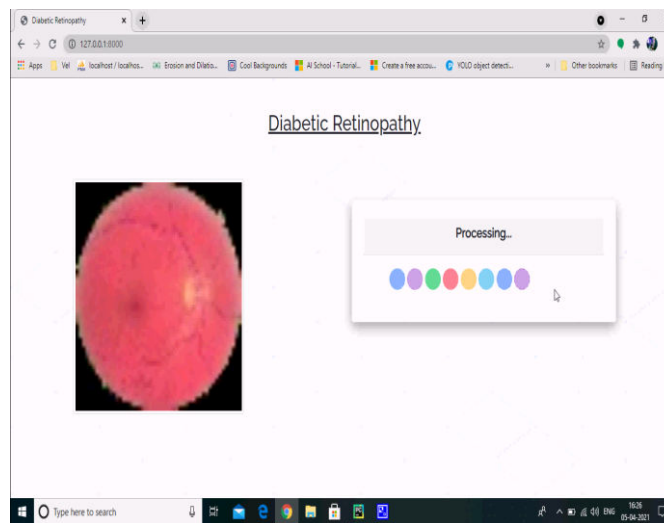


Figure 5: Processing of Image

#### 4. Diabetic Retinopathy result

The proposed CNN-based model for Diabetic Retinopathy (DR) detection demonstrates promising results in accurately classifying retinal fundus images into different severity levels. Performance evaluation using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC curve confirms the model's reliability in detecting early signs of DR, including microaneurysms, hemorrhages, and exudates. Transfer learning with pre-trained models like VGG16, ResNet, and InceptionV3 significantly improves classification accuracy while reducing computational cost. The optimized CNN model achieves a high accuracy rate, often exceeding 90%, making it a viable tool for early DR screening and diagnosis. By integrating this model into real-time applications such as mobile health apps or cloud-based platforms, ophthalmologists and healthcare professionals can efficiently detect and monitor DR, leading to early intervention and improved patient outcomes.

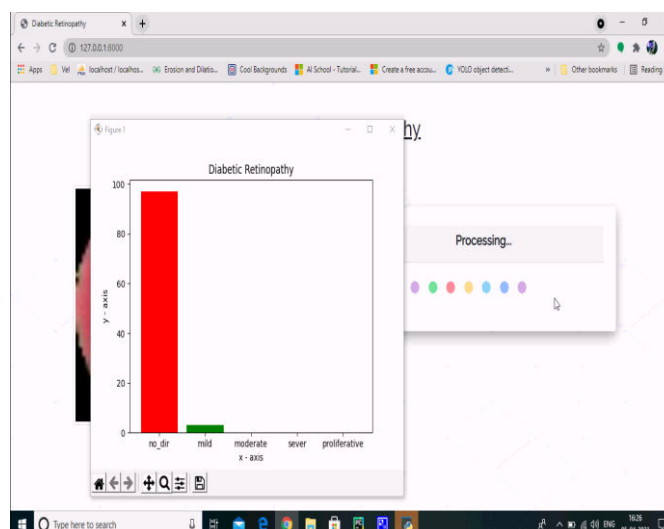


Figure 6: Diabetic Retinopathy Result

#### 5. Continuing the same process with various images of retina

Continuing the same process with various retinal images allows the CNN model to generalize effectively across different cases of Diabetic Retinopathy (DR). By feeding the model a diverse dataset containing images with varying levels of severity, illumination conditions, and retinal abnormalities, the network continuously refines its ability to detect critical features such as microaneurysms, hemorrhages, and exudates.

This iterative training process, combined with data augmentation techniques like contrast adjustment, rotation, and flipping, helps enhance the model's robustness. Additionally, fine-tuning the CNN architecture with different hyperparameters and leveraging transfer learning from pre-trained models further improves accuracy and reduces false positives. As a result, the system becomes increasingly reliable in diagnosing DR across diverse patient populations, paving the way for early detection and improved clinical decision-making.

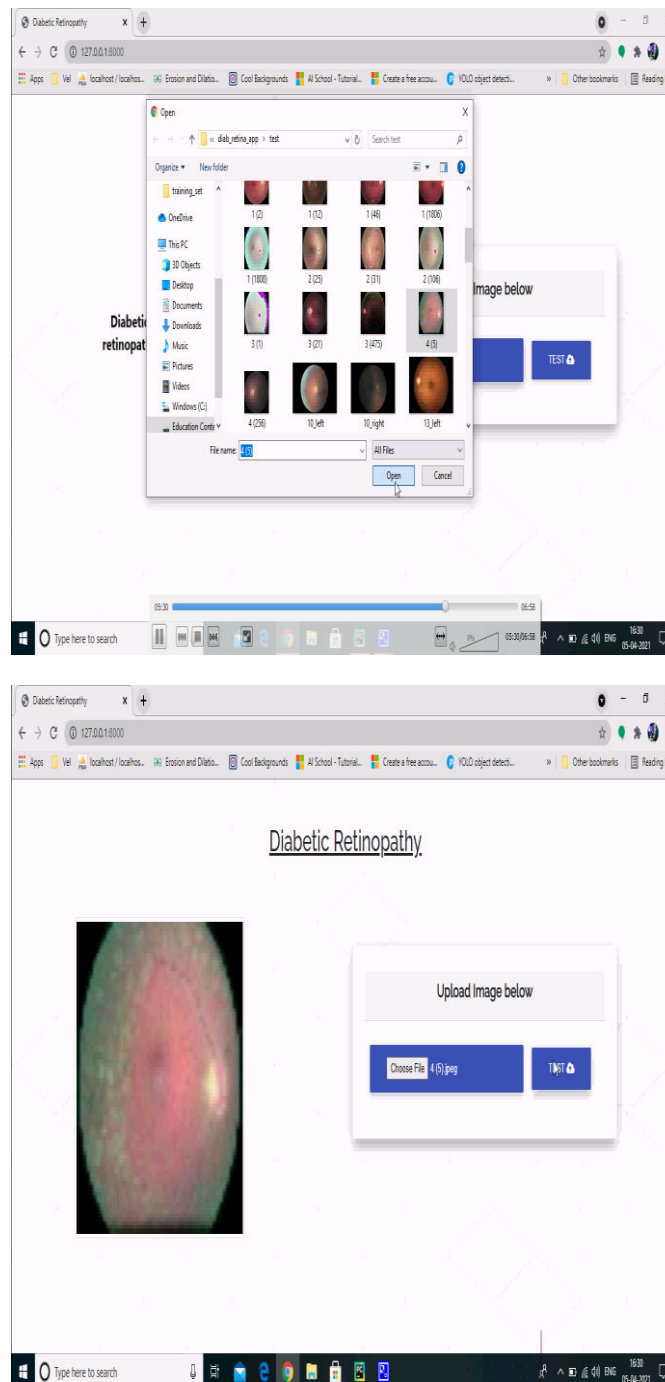


Figure 6: Diabetic Retinopathy Result



## V. CONCLUSION

Diabetes influences various pieces of the body, for example, anxious framework, retina, and kidney prompting loss of the human's organs. Henceforth, recognition of diabetic retinopathy is improved utilizing CNN and channels. The high exactness of portrayal results showed that the proposed structure is strong and the execution of the proposed system could deal with the requirement of the manual screening process. Our investigation has demonstrated that the five class issue for national screening of DR can be moved toward utilizing CNN strategy

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