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Deep Learning -Based Diabetic Retinopathy Detection and Severity Classification using CNN ResNET.

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Abstract- ***Diabetic Retinopathy (DR) is an ocular complication associated with diabetes and remains one of the primary contributors to vision impairment among the working-age population. The condition arises when prolonged high blood glucose levels damage the retinal blood vessels, causing them to dilate, leak fluids, or obstruct normal circulation. As the disease advances, it can lead to severe visual decline or even complete blindness. The central aim of this research is to enable early detection of DR by applying machine learning approaches and to classify retinal images into five distinct stages: No DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR. Effective categorization of such medical images is facilitated through the use of a Convolutional Neural Network (CNN) architecture.***

Keywords: Diabetic Retinopathy, Fundus Imaging, Artificial Intelligence, Convolutional Neural Network, Proliferative DR, Non-Proliferative DR, Visual Impairment.

I. INTRODUCTION

Diabetes has become a major health concern worldwide, with nearly 285 million individuals currently living with this condition. It impacts almost every organ of the human body, and one of the serious complications is Diabetic Retinopathy (DR). This disorder, often referred to as “Diabetic Eye Disease”, can result in severe vision loss or complete blindness. When a person develops diabetic retinopathy, the blood vessels of the retina begin to deteriorate and sustain damage, as illustrated in the figure below.

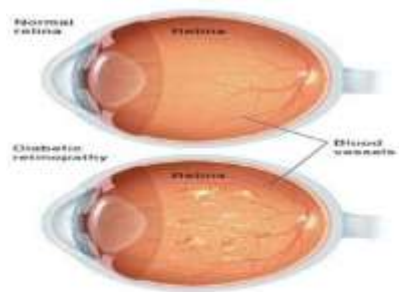

Fig. 1 Variation in blood vessels

When diabetes impacts the eye’s small blood vessels, they may become fragile, rupture, and leak, causing fluid accumulation in the macula. Over time, this vascular damage leads to gradual decline in vision. In the early stages, the condition often progresses silently without noticeable signs, but as it advances, patients may begin to experience visual disturbances. Therefore, identifying diabetic retinopathy at its onset is essential to prevent severe sight loss. Retinal fundus photography has become a key tool in diabetes management, as fundus images are commonly employed for detecting such complications.

In this study, a Convolutional Neural Network (CNN) framework is employed to analyze retinal fundus images, either captured with a 20D smartphone-based lens or directly uploaded by users. Prior to analysis, the images undergo preprocessing operations such as intensity adjustment and augmentation to enhance quality. The refined images are then processed by a CNN with a ResNet backbone, which extracts critical retinal patterns required for accurate recognition. The final classification module determines whether diabetic retinopathy is present and assesses its severity. Clinically, DR is typically classified into two major categories: Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR).

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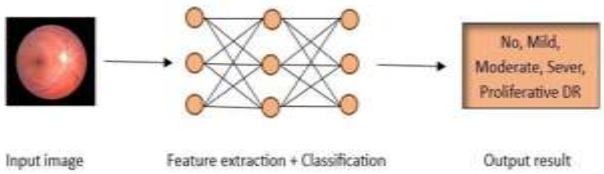

Fig. 2 Image classification using CNN

The dataset consists of 3,500 color retinal fundus photographs, systematically divided into five diagnostic categories:

- Class 0 – No DR: Represents a healthy retina with no visible abnormalities or disease indicators.
- Class 1 – Mild DR: The earliest stage, characterized by the appearance of small bulges in retinal capillaries, known as microaneurysms, typically located close to the retina.
- Class 2 – Moderate DR: At this level, the condition advances, and several retinal vessels that provide oxygen and nutrients become partially or fully obstructed.
- Class 3 – Severe DR: A more advanced stage where a significant proportion of retinal blood vessels are blocked, restricting circulation. The oxygen-deprived retinal regions respond by releasing biochemical signals that stimulate the formation of new vessels.
- Class 4 – Proliferative DR: The most critical stage of the disease. Here, abnormal new vessels (neovascularization) emerge in response to the retina's need for nourishment. Although these vessels may not cause immediate vision loss, they are extremely fragile and prone to leakage. Hemorrhages caused by these delicate vessels can result in major vision impairment, and in severe cases, irreversible blindness.

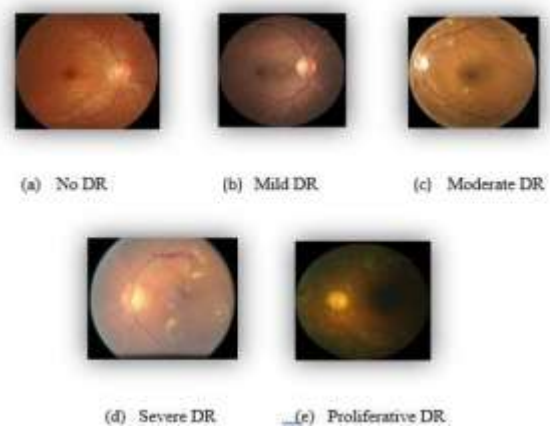

Fig. 3 The five Diabetic Retinopathy stages

II. METHODOLOGY

The methodology adopted in this study is organized into three primary stages: preprocessing, feature extraction, and classification. Initially, retinal fundus images are acquired either from publicly available datasets or directly from diabetic individuals. These images undergo a preprocessing pipeline that includes intensity normalization and augmentation techniques to improve data quality and enhance model generalization. The ImageDataGenerator function from Keras is employed for this purpose, enabling various transformations such as rotations, flips, translations, zooming, and shearing, along with normalization and rescaling. In addition, all images are standardized by resizing and compressing them into a consistent format for uniform processing.

In the next stage, feature learning is performed using a Convolutional Neural Network (CNN) built on the ResNet framework, which automatically extracts discriminative retinal features. Based on these extracted patterns, the system assigns each image to one of the five diagnostic categories: No DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR. Finally, the complete workflow of the proposed diabetic retinopathy detection system, outlining the sequence of steps from image acquisition to classification, is illustrated in Figure 4.

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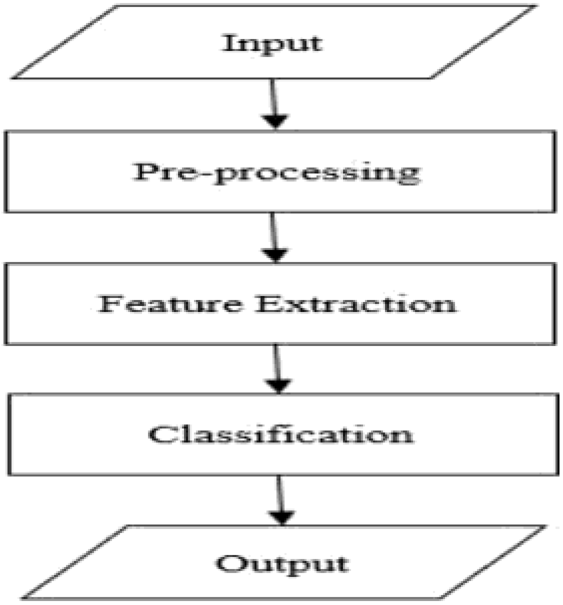

Fig.4 Flow diagram

By adopting this framework, a dependable deep learning–based system for diabetic retinopathy detection can be developed. The process is structured into the following stages:

Data Collection:
A sufficiently large and diverse dataset of retinal fundus images is assembled, covering the full spectrum of diabetic retinopathy severity. This ensures representation across normal, mild, moderate, severe, and proliferative cases.

Data Preprocessing:
All images are standardized by adjusting them to a fixed resolution and normalizing their pixel intensities. To mitigate class imbalance and improve generalization, data augmentation strategies such as rotation, flipping, and scaling are applied to enlarge the dataset and introduce variability.

Model Selection:
For image-based classification tasks, a Convolutional Neural Network (CNN) is employed owing to its proven efficacy in extracting hierarchical visual features. The chosen network serves as the backbone of the system.

Model Training:
The CNN is trained using the preprocessed dataset with an appropriate loss function and optimizer. Training is carried out over multiple epochs to iteratively refine the network’s weights and improve accuracy.

Model Evaluation:
System performance is assessed on an independent test set using key metrics including accuracy, precision, recall, and the F1-score, thereby validating its generalization capability.

Model Optimization:
Further refinements are introduced by tuning hyperparameters such as learning rate, batch size, and number of epochs, which stabilize training and improve predictive performance.

Model Deployment:
The optimized model is integrated into a practical platform—either web-based or mobile—facilitating user-friendly access for clinicians and patients.

Performance Monitoring:
Finally, the deployed system is continuously monitored in real-world settings. Feedback from users and clinical outcomes is incorporated to iteratively enhance its reliability and applicability.

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III. SYSTEM ARCHITECTURE

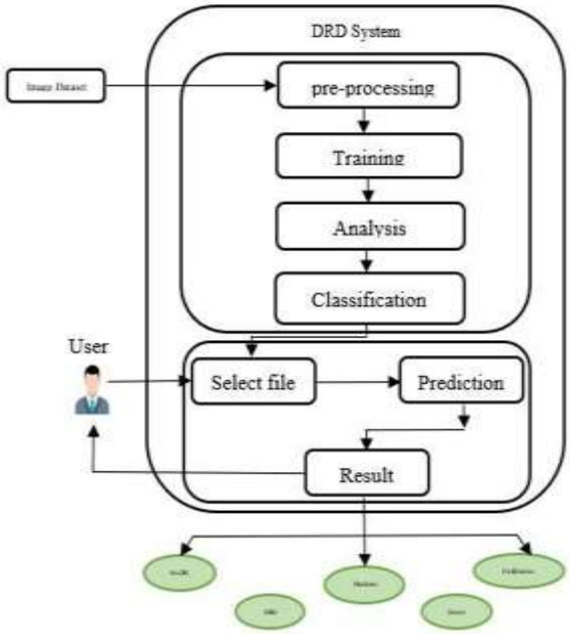

Fig.5 Architecture of Diabetic Retinopathy System

The proposed framework for detecting diabetic retinopathy is organized as a multi-stage pipeline, illustrated in the system diagram. The process begins with the acquisition of retinal fundus photographs, which are first standardized since raw images collected from hospitals or screening centers often vary in resolution and quality. After this cleaning step, the images are prepared for model training. In this study, a residual network with 18 layers (ResNet18) is employed as the feature extractor, and its output is passed to a convolutional network that performs the final categorization. Rather than a binary outcome, the system distinguishes among different levels of disease severity, ranging from a completely healthy retina to progressively worsening stages that ultimately include advanced proliferative retinopathy.

When a retinal image is submitted—either uploaded from storage or captured using a fundus camera—the system preprocesses it through resizing, intensity normalization, color/grayscale conversion, and filtering to minimize artifacts. The learning stage relies on a curated dataset in which ophthalmologists have annotated images according to the degree of retinopathy present. Using this reference information, the network gradually learns to highlight discriminative visual markers associated with each disease stage. The workflow starts with dataset preparation, followed by systematic preprocessing to correct inconsistencies. Once processed, image features are extracted and analyzed, enabling the model to generalize its predictions to new, unseen cases with a high degree of reliability.

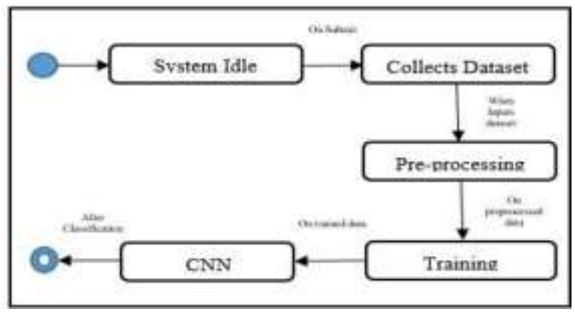

Fig.6 State Diagram of Training DRS

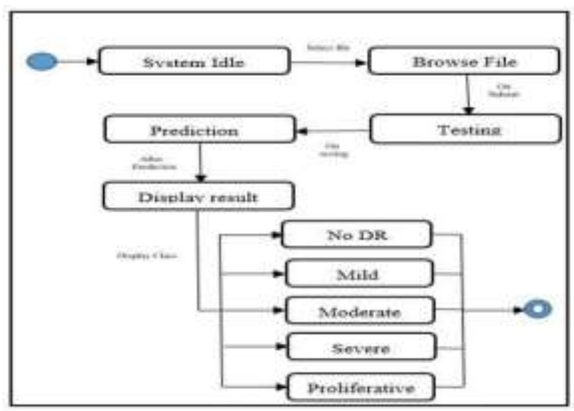

Fig.7 State Diagram Testing of DRS

Initially, the system remains in an idle state. Once the administrator browses and selects the specified file, the data is collected. The acquired dataset is then examined to eliminate any missing or null values. After preprocessing, the refined data is categorized into specific classes, which serve as the basis for prediction using TensorFlow and Keras libraries. Finally, the system is evaluated to produce the required output according to the inputs provided by the user.

III. RESULTS AND DISCUSSION

The performance of the deep learning model for diabetic retinopathy detection is assessed using accuracy, sensitivity, specificity, and the area under the Receiver Operating Characteristic (ROC) curve. Accuracy indicates the ratio of correctly predicted images to the total number of images in the dataset. Sensitivity reflects the model's capability to correctly identify positive cases, while specificity demonstrates its ability to correctly recognize negative cases. The area under the ROC curve (AUC) serves as an overall indicator of model effectiveness, representing the balance between sensitivity and specificity.

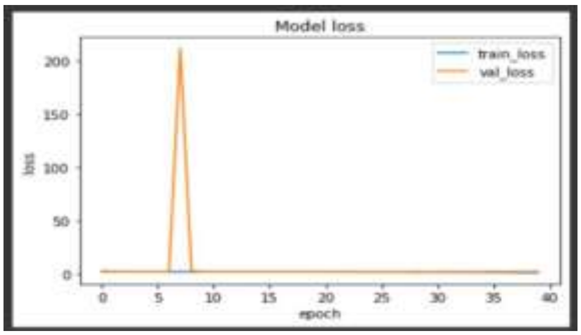

Fig. 8

Figure 8 illustrates that the preparation of both the training and validation data has been carried out correctly. Because of this proper formatting, the network shows only a small error rate throughout the learning and evaluation stages. A concise overview of the resulting performance is provided below.

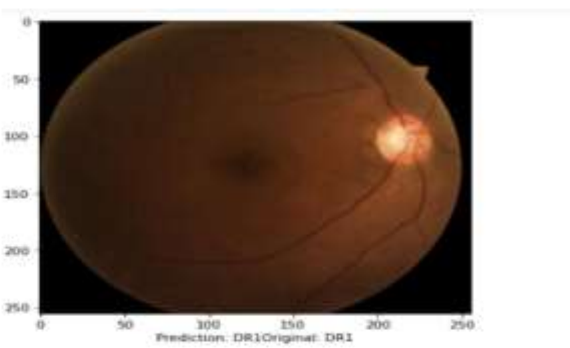

Fig. 9

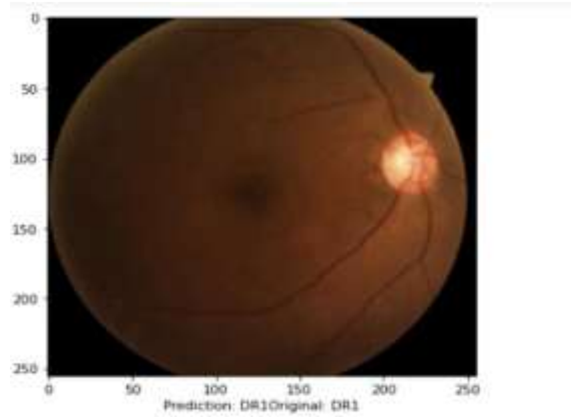

Fig. 10

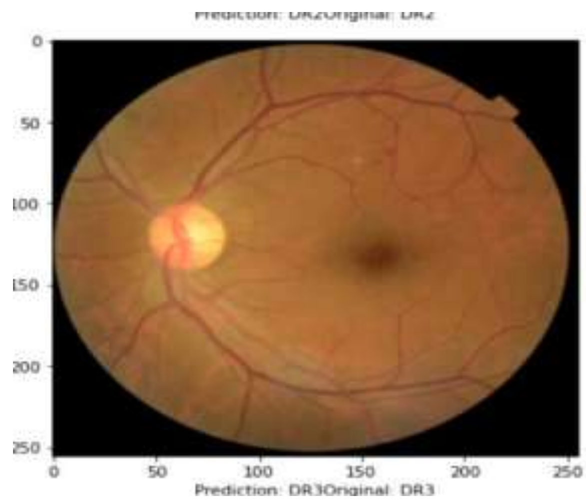

Fig. 11

In Figures 9, 10, and 11, the comparison between the training and testing datasets is illustrated. The figures demonstrate that the predicted results align closely with the original labels, indicating that the model achieves a high level of accuracy and performs efficiently.

IV. CONCLUSION

This Diabetic Retinopathy Detection System facilitates the early identification of DR, thereby reducing the risk of vision loss or complete blindness. The approach not only minimizes the time and cost associated with diagnosis but also enables healthcare professionals to manage a larger number of patients efficiently while reducing the need for frequent visits to eye specialists. Looking ahead, the system can be further enhanced by improving its accuracy and making it more accessible through deployment as a mobile application or a web-based platform.

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REFERENCES

[1] B. S. Fernando, H. F. A. S., A. M., and J. R., “Diabetic Retinopathy Detection Using Retinal Images,” International Journal of Applied Engineering and Management (IJAEM), Mar. 2021.

[2] A. Kokane, G. Sharma, A. Raina, S. Narole, and P. Chawa, “Detection of Diabetic Retinopathy using Machine Learning,” International Research Journal of Engineering and Technology (IRJET), Nov. 2020.

[3] S. Padhy, B. Takkar, R. Chawla, and A. Kumar, “Artificial intelligence in diabetic retinopathy: A natural step to the future,” Indian Journal of Ophthalmology (IJO), Jul. 2019.

[4] M. S. B. and H. S. Sheshadri, “Analysis of Detection of Diabetic Retinopathy using LBP and Deep Learning Techniques,” International Journal of Engineering Trends and Technology (IJETT), Dec. 2020.

[5] M. Z. Atwany, A. H. Sahyoun, and M. Yaqub, “Deep Learning Techniques for Diabetic Retinopathy Classification: A Survey,” IEEE Access, Mar. 2022.

[6] T. N. Anitha, B. K., and Jhalkee, “Diabetic Retinopathy Detection and Classification,” May 2022.

[7] A. Bilal, G. Sun, and S. Mazhar, “Survey on recent developments in automatic detection of diabetic retinopathy,” Mar. 2021.

[8] Y. Kumaran and C. M. Patil, “A Brief Review of the Detection of Diabetic Retinopathy in Human Eyes Using Pre-Processing & Segmentation Techniques,” International Journal of Recent Technology and Engineering (IJRTE), Dec. 2018.

[9] X.-N. Wang, L. Dai, S.-T. Li, H.-Y. Kong, B. Sheng, and Q. Wu, “Automatic Grading System for Diabetic Retinopathy Diagnosis Using Deep Learning Artificial Intelligence Software,” May 2020.

[10] L. Dai, L. Wu, H. Li, C. Cai, Q. Wu, H. Kong, R. Liu, X. Wang, X. Hou, Y. Liu, X. Long, Y. Wen, L. Lu, Y. Shen, Y. Chen, D. Shen, X. Yang, H. Zou, B. Sheng, and W. Jia, “A Deep Learning System for Detecting Diabetic Retinopathy Across the Disease Spectrum,” 2021.

[11] Y. R., R. S. M., R. Panjanathan, G. J. S., and J. A. L., “Diabetic Retinopathy Classification Using CNN and Hybrid Deep Convolutional Neural Networks,” Symmetry, Sep. 2022.

[12] J. Amin, M. Sharif, and M. Yasmin, “A Review on Recent Developments for Detection of Diabetic Retinopathy,” Sep. 2016.