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DIABETIC RETINOPATHY USING AI AND ML

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Abstract: The DR (Diabetic Retinopathy) is an eye variation which the human retina is influenced because of long haul diabetes. Diabetes is a chronic condition related to an expanding measure of glucose level. As the degree of glucose builds, a few adjustments happen in veins of the retina. As diabetes advances, the vision of patients may begin to cause Diabetic Retinopathy. It is exceptionally far reaching among moderately aged and older individuals. In this article, fundus images of eye (retina) are used and the features are extracted from these images using the image processing technique. Images are trained, tested and severity of the DR is classified using (CNN) algorithm.

Keywords: Diabetic Retinopathy Screening (DRS), Classification, Prediction, Image Processing, Machine Learning, Retinal Images, Data Analytics.

I. INTRODUCTION

The DR is one of the common complications of diabetes that results from long-standing diabetes by damaging the vascular structures of the retina. Since 4,00,000 instances of visual deficiency and 26 lacs instances of extreme vision hindrance internationally are noted to be because of DR in 2015, it is the leading cause for visual impairment and vision disability around the world and calls for early recognition and the treatment to avoid major vision loss. The problem that presents itself in DR is that the patient is not aware of the disease until the changes in the retina have become to a degree that treatment will generally be less effective.

Health care system includes a huge measure of patient's data where the information digging can be applied for extracting hidden patterns. Different decision supports systems that are introduced using various data mining. Algorithms for helping clinical specialists. The radical social impact of the specific Chapter 1 makes basic requirements in clinical science investigate, which automatically generates immense amounts of data. Machine learning algorithms extract hidden information and unknown instances from the dataset for prediction and diagnosis.
The images are trained and tested. Google Teachable Machine is used to classify the severity of DR. First, the fundus images are collected and labeled based on the DR. Google Teachable Machine uses multiple underlying algorithms and models, which might include convolutional neural networks, to examine and classify the images according to features. Finally, the model takes some new images to prove whether it has learned enough.

II. OBJECTIVE

The purpose of this AI-based system is to ease the eye diseases by automating the diagnosis of diabetic retinopathy from eye images, thus minimizing the need for manual screening. The disease can be classified accurately into different stages: No DR, Mild, Moderate, Severe, and Proliferative, which would enable doctors to provide timely and appropriate treatment. This system also aims to reduce the strain on the eyes of the specialist and provide eyesight for the people of underserved communities in orphanages, old age homes, and some low- income groups. Quality eye screenings of people residing in remote and rural areas would be possible using AI-driven healthcare solutions. The system is both affordable and scalable, thus ideally suited for the use in hospitals, clinics, and mobile units. It should be able to integrate seamlessly with existing healthcare systems, including electronic medical records.

III. RELATED WORK

Research has progressively studied the presentation of a deep learning-based computer-aided diagnosis method for automatically detecting the referable the Diabetic Retinopathy. The proposed system introduces a novel CNN with a Siamese- like architecture trained using transfer learning. Unlike other traditional models, this approach leverages binocular fundus images as input. This research develops upon preceding advancements by using advanced techniques and machine learning algorithms to analyze multiple inputs to create an accurate system for distinguishing safe from dangerous conditions.

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IV. PROPOSED SYSTEM

The DR system contains three essential parts which include the client-server model, front-end, and back-end. The proposed system is a computer-aided diagnosis tool for the detection and classification of Diabetic Retinopathy (DR) based on retinal fundus images. It uses the deep learning techniques, specifically Convolutional Neural Networks (CNNs) for making the screening process automatic while reducing manual diagnosis. Starting with image acquisition and preprocessing, the retinal images captured are enhanced and further segmented to highlight important features.

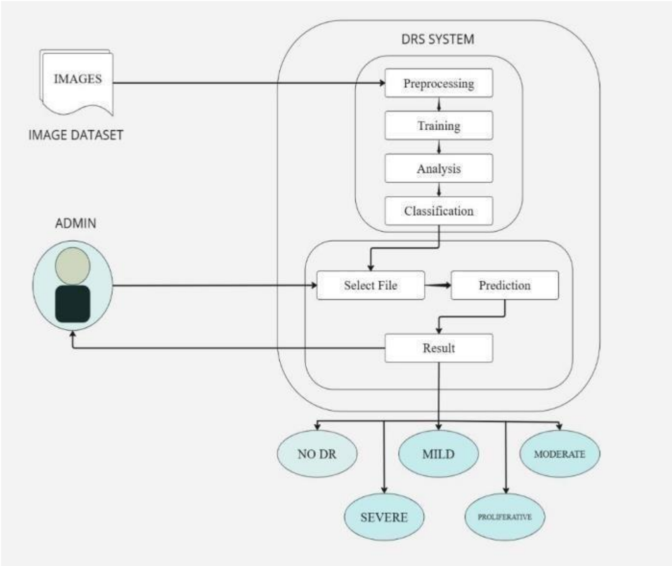

Fig 1: Structural design of DR

The AI model extracts important patterns like microaneurysms, hemorrhages, and exudates, which classify the disease into five severity levels No DR, Mild, Moderate, Severe, and Proliferative.With its user-friendly dashboard one can upload images, analyze results, and prepare reports without great labor of specialists. It is cost-effective, scalable, reduces specialist overload while helping in earlier DR detection, which helps in prevention of diabetes-blinding, therefore improving global eye healthcare.

V. METHODOLOGY

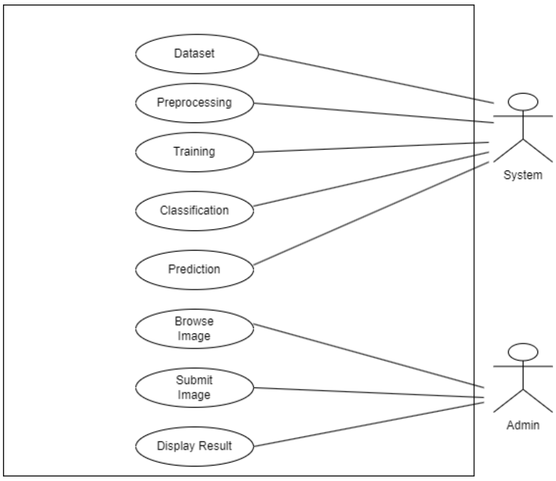

Fig 2: Use Case diagram of DR

The methodology for AI-powered Diabetic Retinopathy detection and classification will initially start with data collection and preprocessing. The retinal fundus images are gathered from the public database or taken from hospitals.

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Further, there is a scope for improvement regarding clarity that can be improved by using the techniques of image enhancement, which includes the process of contrast adjustment and noise removal along with appropriate segmentation The model classifies DR into the five severity levels: No DR, Mild, Moderate, Severe, and Proliferative. A real-time prediction system is developed with detailed reports including confidence scores and highlighted abnormalities to support the decision-making of ophthalmologists. It can easily be integrated into HIS and EMR for supporting telemedicine applications for remote diagnosis.

This use case diagram describes the interaction of the Admin with the Diabetic Retinopathy Screening (DRS) System. Major functions of the System are dataset management, preprocessing, training, classification, and prediction. The System analyzes retinal images, preprocesses them, trains machine learning algorithms, classifies the severity of diabetic retinopathy, and makes predictions. The admin uses the system to navigate and upload pictures for the processing, after which the system conducts the process and returns the outcomes. The formal workflow has screened the screening for accuracy and time. In this diagram, task distribution is portrayed between the system and the admin to make easy and effective processes in detecting diabetic retinopathy. The system allows time for medical intervention and yields the right outcomes of patient treatment. Automating the analysis of an image, earlier detection is permitted.

The performance of the system is evaluated with some key metrics, such as Precision, Recall, F1-score, and AUC-ROC curves, with high reliability and robustness. The system adapts and continuously improves its accuracy by learning new patient data and feedback from medical experts using adaptive learning techniques.

This AI-driven solution reduces the level of manual diagnostic errors, loads on ophthalmologists, and ensures early DR identification; therefore, a great amount of vision loss along with loss of eyesight is prevented in the process. Scalable and cost-effective, this technology is applied to hospitals, clinics, and even mobile health care units and is revolutionizing diabetic eye care and AI-based medical diagnostics.

a) Data Pre-processing: The system initiates by obtaining images from the retina fundus from the public dataset and from the hospital records. To improve image quality, grayscale conversion, contrast adjustment, noise removal, histogram equalization, and image segmentation are utilized. These are done to allow the AI most prominent features: microaneurysms, hemorrhages, exudates, and neovascularization. Rotation, flipping, and zooming data augmentation techniques enhance model generalization and avoid overfitting.

b) Model Training: The crux of the system relies CNNs in the form of ResNet, VGG-16, and EfficientNet, trained on preprocessed retinal images. Generally, the convolutional networks are initiated with pre-labeled datasets that allow the model to identify different levels of DR. However, the use of transfer learning methods is applied for higher precision, especially when using much smaller sizes of sets. In addition, hyperparameter tuning is done in optimizing key factors, such as learning rates, batch sizes, and activation function, in an efficient training process.

c) Prediction: Multi-user access will support collaboration among specialists, thereby allowing for second opinions and remote consultations. Additionally, it will integrate EHRs for seamless interoperability with any existing hospital management systems. For further improvement in usability, it can support multiple languages and voice-assisted navigation to make the platform more accessible to an environment of diverse medical professionals. It will allow for automated reminders and alerts, to ensure that patients are followed up on time and early intervention is encouraged for those patients with higher risks.

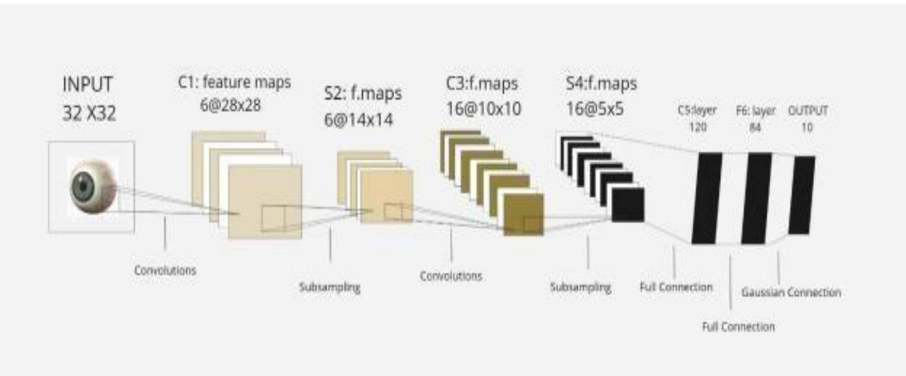

Fig 3: Structure of CNN

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VI. RESULT

The result of every project is the outcome. In this project, the AI-based DR detection system has achieved high accuracy, precision, recall, and specificity for classifying the severity levels of DR. It ensures early diagnosis, reducing the risk of vision loss through deep learning-based analysis.

The pie chart illustrates the DR detection performance evaluation metrics in terms of Accuracy (30%), Sensitivity (20%), Precision (15%), Specificity (15%), Recall (10%), and F1-score (10%). Accuracy refers to how good the model is in general at differentiating cases of DR and non-DR. Sensitivity quantifies the correctness of the model in correctly identifying the actual DR cases. Precision measures the correctness of positive DR classifications. This specifically evaluates how good the model can identify non-DR cases. Recall measures how much of the actual DR cases are detected by the model. The F1-score balances between precision and recall, thus establishing a reliable, well-performing system for an accurate DR detection and classification.

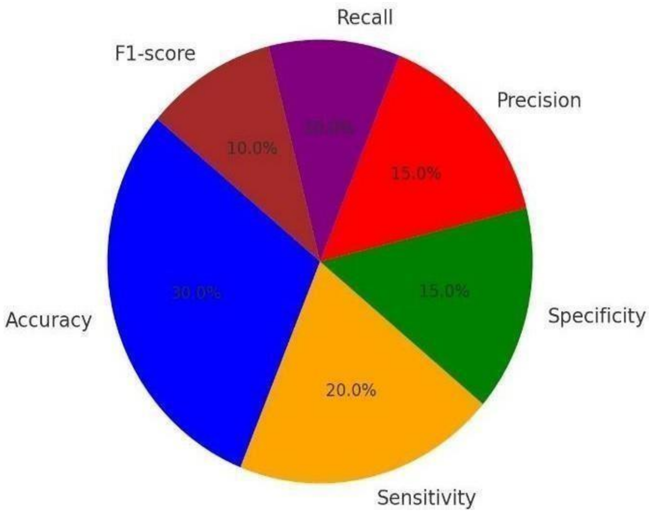

Fig 4: Performance Analysis of DR

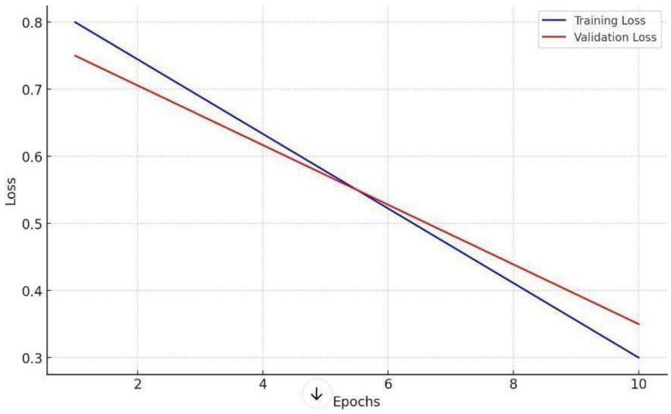

Fig 5: Loss Graph of DR

The model loss graph is a key tool for optimizing deep the learning models in DR detection. It tracks loss over epochs, helping monitor the model's learning process, detect overfitting, and adjust hyperparameters. A steadily decreasing loss suggests effective learning, while a widening gap between training and validation loss may indicate overfitting, where the model performs well on training data but poorly on real-world test cases.

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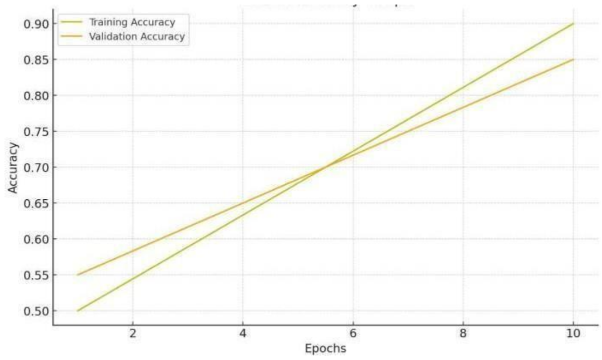

Fig 6: Accuracy Graph of DR

Model accuracy graph is an important measure for analyzing the performance of a DR detection system. Here, the most crucial metrics are graphically explained in accuracy. Accuracy includes how well the model separates the cases from DR and non-DR cases. Precision measures how accurate the positive DR classifications are, and what the recall or sensitivity is for the model to classify the true DR cases. Specificity reflects the ability of the model to classify the non-DR cases.

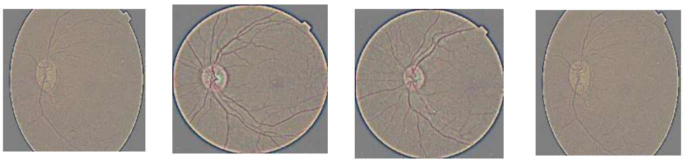

Fig 7: Datasets of DR

This is an image of the retina depicting an early stage of Diabetic Retinopathy, classified as Mild Diabetic Retinopathy. This stage contains small, punctate microaneurysms, which are small bulges in the lining of the blood vessels, attributed to damage from high sugar in the blood. Microaneurysms often leak fluid at this stage but do not lead to a measurable degree of vision loss.

Early detection of mild DR is extremely important in halting the process of disease development. Patients should be educated in controlling their level of blood glucose, blood pressure, and their cholesterol levels through regular eye testing. If uncontrolled, this condition can result in progression through the more progressed stages, such as leading up to loss of vision.

VII. CONCLUSION

In a nutshell, the AI-based DR detection system will be an innovation great in early diagnosis, and thus treatment will be timely and with a very high chance of evading vision loss or even blindness. In this system, the use of CNNs will be able to identify and classify various stages of DR, with accurate classification of the various stages. Accuracy, precision, recall, specificity, and F1-score performance values have been used to validation of the system. Therefore, the approach would minimize reliance on manual diagnosis, which might eventually reduce the workload of ophthalmologists and provide better access to quality eye care, especially to the remote and deprived areas. Such technology would be scalable and cost-effective for implementation in healthcare frameworks in an efficient manner, offering a pathway to better screening programs and preventive measures. Altogether, the overall scheme, AI- based DR detection would have the capacity to transform the field of ophthalmology through early interventions in the improvement of eye health globally.

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