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Diabetic Retinopathy detection using CNN-Based Image Processing and Machine Learning

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Abstract: Diabetic Retinopathy (DR) is a progressive eye disease that can lead to permanent blindness if not detected early. Traditional diagnostic methods, though effective, are timeconsuming and may cause discomfort to patients. This project proposes an automated system for early DR detection by leveraging Convolutional Neural Networks (CNNs) and machine learning classifiers. Key features such as optic disk diameter, microaneurysms, exudates, and other image-level characteristics are extracted through advanced retinal image processing techniques. CNNs are used for automated feature extraction and classification, while traditional classifiers like Alternating Decision Trees, AdaBoost, Naïve Bayes, Random Forest, and Support Vector Machines (SVM) are integrated to enhance detection performance. The goal is to develop a highly accurate, efficient, and reliable tool for early DR screening, offering a fast and non-invasive alternative to conventional diagnostic approaches .

Keywords: Diabetic Retinopathy (DR), Convolutional Neural Networks (CNNs), Retinal Image Processing, Machine Learning

I. INTRODUCTION

Sepsis is a potentially life-threatening condition that develops in response to the body's massive immune response to infection, which can quickly progress to tissue damage, organ failure, and death if not treated promptly. Outdated detection approaches rely on clinical observation and laboratory diagnosis, leading to poor prognosis and a late response to treatment. Healthcare has even opened many new doorways of earlier discovery and productive care for such severe diseases with the help of Machine Learning .

Diabetic Retinopathy (DR) is one of the leading causes of blindness among working-age adults worldwide. It is a complication of diabetes that affects the retina, the light-sensitive tissue at the back of the eye. If not detected and treated in time, it can lead to irreversible vision loss.

Traditional diagnosis of DR involves manual inspection of retinal fundus images by ophthalmologists. This process is time-consuming, subject to human error, and not scalable for mass screening, especially in regions with limited access to eye care specialists.

With the advancement of deep learning, particularly Convolutional Neural Networks (CNNs), there is a growing interest in automating the detection of DR. In this project, we utilize ResNet50, a powerful CNN architecture, to classify retinal images and detect signs of diabetic retinopathy accurately.

This system aims to assist healthcare professionals by providing a faster, more consistent, and scalable method for early DR detection, ultimately helping prevent vision impairment in diabetic patients.

Problem Definition

Diabetic Retinopathy (DR) is a common complication of diabetes that can lead to permanent vision loss if not diagnosed and treated early. The traditional method of diagnosing DR involves a manual examination of retinal fundus images by ophthalmologists, which has several limitations:

- It is time-consuming and resource-intensive.
- It is prone to subjective interpretation and diagnostic variability.

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- There is a shortage of trained specialists, especially in remote or underdeveloped regions.

Given the growing global diabetic population, there is a need for a reliable, automated, and scalable solution to assist in DR detection.

This project aims to address the following problem:
How can we leverage deep learning, specifically the ResNet50 CNN architecture, to automatically detect diabetic retinopathy in retinal fundus images with high accuracy and minimal human intervention?

The scope of this project includes the design, training, and evaluation of a deep learning model for diabetic retinopathy detection. Key aspects include:

Data Source: Use of publicly available, labeled fundus image datasets from Kaggle's Diabetic Retinopathy Detection challenge.

Model Architecture: Implementation of ResNet50, a pre-trained convolutional neural network known for its depth and accuracy in image classification.

Preprocessing Techniques: Image resizing, normalization, data augmentation to improve generalization.

Training and Validation: Splitting the dataset to evaluate model performance and avoid overfitting.

Evaluation Metrics: Accuracy, confusion matrix, precision, recall, F1 score.

Classification Objective: Detect and classify images into different stages of diabetic retinopathy (e.g., No DR, Mild, Moderate, Severe, Proliferative DR).

Practical Impact: Provide a tool that can support ophthalmologists and serve as a first-level screening system in healthcare settings.

II. RELATED WORKS

In ***[1], A. Gulshan et al. (2016)*** : This pioneering study by Google Research introduced a deep convolutional neural network using the InceptionV3 architecture for the automated detection of referable diabetic retinopathy (DR) from retinal fundus photographs. The model was trained end-to-end on a large-scale dataset of over 128,000 annotated images sourced from EyePACS and Messidor-2, incorporating multiple expert opinions to establish a robust ground truth. Unlike traditional screening methods, which are manual, time-consuming, and prone to inter-observer variability, this approach offered a scalable and consistent solution. The system achieved a sensitivity of 90.3% and a specificity of 98.1%, comparable to board-certified ophthalmologists. It also demonstrated the feasibility of integrating AI into clinical workflows for mass DR screening, especially in areas with limited access to trained eye care professionals. This research laid the foundation for subsequent developments in AI-based medical diagnostics and is considered a landmark study in the field of ophthalmic AI

In ***[2] P. Pratt et al. (2016) :*** This research focused on using deep CNNs to classify fundus images into five severity levels of diabetic retinopathy. The study employed a multi-layer CNN architecture trained on the Kaggle Diabetic Retinopathy Detection dataset, highlighting the importance of image preprocessing such as grayscale conversion and histogram equalization to improve model input quality. The model demonstrated approximately 75% classification accuracy, showcasing the capability of CNNs to learn complex retinal features associated with different DR stages. This work emphasized the potential of deep learning to support automated and scalable DR diagnosis

In ***[3], M. Kaur and R. Kaur (2018)*** : In this study, the authors proposed a deep learning framework for automated DR diagnosis that combined extensive image preprocessing—including contrast enhancement, resizing, and normalization—with a

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CNN model trained on the large Kaggle DR dataset. Their approach aimed to improve feature extraction by enhancing image quality, which resulted in an overall accuracy of 85%. The research highlighted the critical role of preprocessing steps and data augmentation to address class imbalance and variability in fundus images, underscoring how these techniques boost CNN performance in medical image classification.

In ***[4] J. Brownlee (2017)*** **:** This study provided an in-depth exploration of applying CNNs and transfer learning models like VGG16 and ResNet50 for diabetic retinopathy staging. Using the Kaggle DR dataset, the research illustrated how leveraging pre-trained models significantly improved both training speed and classification accuracy compared to training CNNs from scratch**.** The work also stressed the importance of data preprocessing techniques such as image cropping and contrast normalization to enhance feature detectability, ultimately achieving high accuracy in multi-class DR classification.

In ***[5], S. Lam et al. (2019)*** : This paper explored the application of transfer learning by fine-tuning the ResNet50 architecture on the Kaggle DR dataset. The authors incorporated dropout and batch normalization to reduce overfitting and improve generalization. The transfer learning approach reduced training time significantly while achieving approximately 92% accuracy in detecting moderate to severe diabetic retinopathy. The study demonstrated the advantage of using pre-trained deep networks, especially when dealing with limited labeled medical image data.

In ***[6] R. Das et al. (2020)*** [6]: This study examined the impact of aggressive data augmentation techniques such as rotation, zoom, and flipping on the performance of CNN models for DR detection. Using the Kaggle DR dataset, the authors showed that these augmentation strategies substantially improved model robustness and generalization, boosting accuracy from 76% to 84%. The research emphasized the importance of addressing dataset imbalance and variability, especially in medical imaging, to avoid overfitting and enhance the reliability of automated diagnosis systems.

In ***[7] T. Wang and Y. Zhang (2021) :***This work presented a comparative evaluation of multiple deep learning architectures—VGG16, ResNet50, and InceptionV3—for diabetic retinopathy classification using the Kaggle dataset. The study applied consistent preprocessing and hyperparameters to ensure fair comparison. Results showed that ResNet50 achieved the best accuracy at 91%, combining model depth with computational efficiency. The authors discussed the trade-offs between model complexity, accuracy, and training time, concluding that ResNet50 provides an optimal balance for practical DR detection tasks.

In ***[8] H. Li et al. (2020) :*** This study proposed an ensemble framework that combined predictions from multiple CNN architectures, including VGG19, ResNet50, and DenseNet, to improve diabetic retinopathy detection accuracy. By using soft voting and stacking ensemble techniques on Messidor and Kaggle datasets, the model enhanced sensitivity to rare and severe DR classes while reducing false positives. The ensemble approach demonstrated improved robustness and generalization compared to individual models, highlighting the potential of hybrid deep learning systems in clinical diagnostics.

In ***[9] A. Sharma and D. Bansal (2021) :*** The authors introduced a hybrid classification system that combines deep CNN feature extraction (based on ResNet) with classical machine learning classifiers such as Support Vector Machines (SVM) and Random Forests. Using the Kaggle DR dataset, this hybrid approach aimed to leverage the feature learning power of CNNs while improving computational efficiency and classification speed via classical classifiers. The method achieved an

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accuracy of approximately 88%, providing an effective alternative to fully end-to-end deep learning models.

Finally, in ***[10], K. Mehta and L. Roy (2022)*** [10] : This study evaluated different ResNet variants (ResNet18, ResNet50, ResNet101) for multi-class retinal disease classification, including diabetic retinopathy, using a combination of Kaggle and IDRiD datasets. By employing transfer learning and fine-tuning techniques, the authors found that ResNet50 offered the best trade-off between accuracy (93%) and training efficiency.

III PROPOSED METHOD

Proposed System Architecture

The proposed system aims to overcome these gaps by utilizing the ResNet50 convolutional neural network architecture with transfer learning, trained on the comprehensive Kaggle diabetic retinopathy dataset. It incorporates advanced preprocessing and data augmentation techniques to enhance model generalization and address class imbalance. By leveraging residual connections, ResNet50 facilitates training of deeper networks, improving feature extraction and classification accuracy.

System Architecture

The diabetic retinopathy detection system architecture is designed to automate the classification of retinal fundus images into various severity levels of diabetic retinopathy using a deep learning model based on ResNet50.

The system consists of a frontend user interface that allows users, such as clinicians or researchers, to upload retinal images easily. These images are sent to the backend server where preprocessing steps like resizing, normalization, and data augmentation are performed to prepare the images for model inference.

The core of the backend is the ResNet50 convolutional neural network, which processes the preprocessed images to extract features and classify them into diabetic retinopathy grades (no DR, mild, moderate, severe, proliferative). The classification results, along with confidence scores, are sent back to the frontend for display.

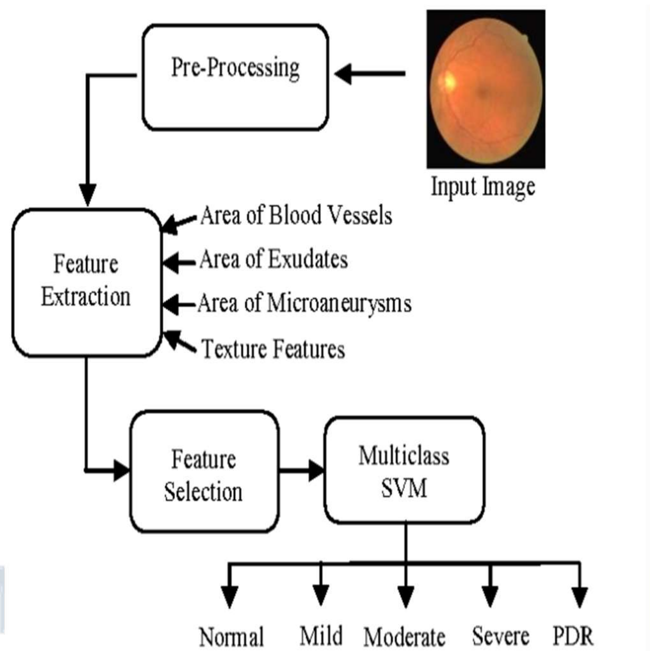

Fig 1: System Workflow

I. Input Image Acquisition:

a. A retinal image is captured using fundus photography or other imaging techniques.

II. Pre-Processing:

a. Enhancing image quality by reducing noise and improving contrast.

b. Normalizing illumination and removing artifacts.

III. Feature Extraction:

a. Extracting key features from the image, including:

b. Blood Vessel Area: Identifying and segmenting retinal blood vessels.

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c. Exudate Area: Detecting bright spots caused by leakage in retinal blood vessels.

d. Microaneurysm Area: Pinpointing small hemorrhages indicative of early-stage diabetic retinopathy.

e. Texture Features: Analyzing patterns and structural variations in the retina.

IV. Feature Selection:

Selecting the most relevant features that contribute to accurate classification.

V. Classification Using Multiclass SVM:

Applying a Support Vector Machine (SVM) algorithm to categorize the condition based on the selected features.

VI. Output Classification:

- The algorithm classifies the retinal condition into one of the following categories:
- Normal: No signs of diabetic retinopathy.
- Mild: Early signs with minimal damage.
- Moderate: Notable retinal abnormalities.
- Severe: Advanced stage with significant damage.
- PDR (Proliferative Diabetic Retinopathy): Critical stage with severe retinal complications.

This project implements an automated diabetic retinopathy detection system using deep learning to assist in the early diagnosis of retinal disease. The core of the system is built around a Convolutional Neural Network (CNN) based on the ResNet50 architecture, which has been fine-tuned using large-scale annotated datasets from sources like Kaggle

Algorithms

This project uses advanced image processing and machine learning algorithms to detect diabetic retinopathy from retinal fundus images. The two key components are Convolutional Neural Networks (CNNs) for feature extraction and classification, and image pre-processing techniques to enhance image quality and improve detection accuracy.

Image Pre-processing

Pre-processing plays a critical role in preparing retinal images for accurate analysis. It helps in reducing noise, improving contrast, and standardizing input for the CNN model.

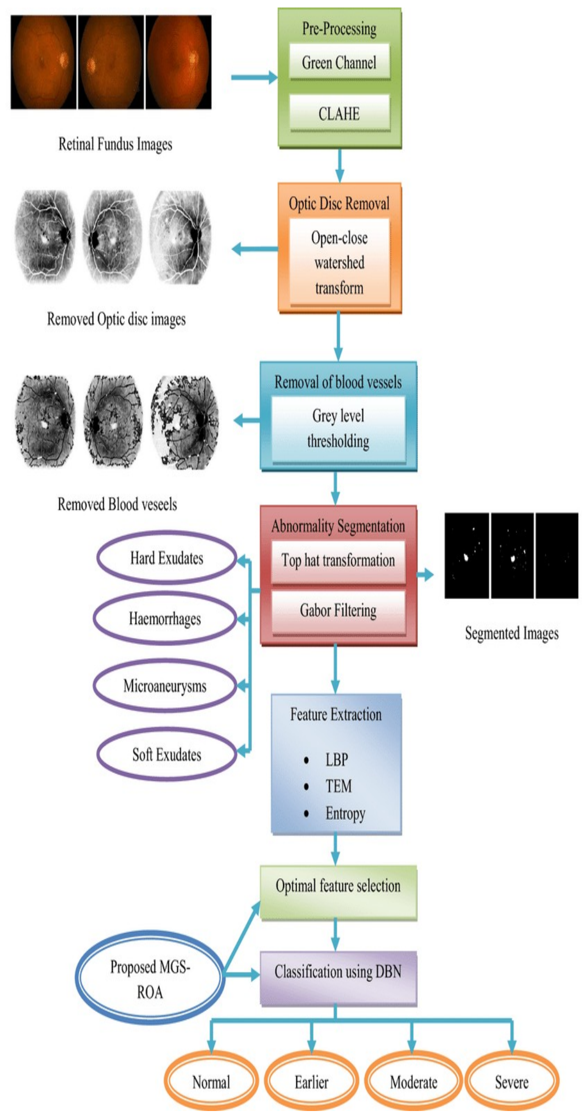

Fig 2: Implementation workflow Algorithms

Steps involved in Pre-processing:

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Resizing: Images are resized to a fixed dimension (e.g., 224x224) to match the input size of the model.

Normalization: Pixel values are normalized to a standard scale (typically 0 to 1) to ensure consistent intensity levels.

Contrast Enhancement: Techniques such as histogram equalization or CLAHE (Contrast Limited Adaptive Histogram Equalization) are applied to highlight retinal features.

Noise Removal: Gaussian blur or median filters may be used to reduce image noise.

Cropping: Background areas are removed to focus only on the retina.

Convolutional Neural Networks (CNNs)

CNNs are deep learning models specifically designed for image recognition tasks. They automatically learn and extract hierarchical features from images, which are crucial for detecting signs of diabetic retinopathy such as microaneurysms, hemorrhages, and exudates.

Main Components of CNN:

Convolution Layer: Applies filters to input images to detect patterns like edges, textures, or lesions.

ReLU Activation: Introduces non-linearity to help the model learn complex patterns.

Pooling Layer: Reduces dimensionality while retaining important features, improving computational efficiency.

Fully Connected Layer: Combines features for final classification.

Softmax Layer: Outputs probability scores for each class (e.g., No DR, Mild, Moderate, Severe, Proliferative DR).

By combining image pre-processing and CNN-based classification, the system can accurately and efficiently detect diabetic retinopathy, assisting in early diagnosis and treatment

IV EXPERIMENTAL SETUP

This project implements an automated diabetic retinopathy detection system using deep learning to assist in the early diagnosis of retinal disease. The core of the system is built around a Convolutional Neural Network (CNN) based on the ResNet50 architecture, which has been fine-tuned using large-scale annotated datasets from sources like Kaggle. The backend is developed in Python 3.8, utilizing essential libraries such as TensorFlow/Keras for model training and prediction, and OpenCV for image preprocessing. The frontend interface is designed using Visual Studio Code with HTML, CSS, and Python-based GUI frameworks (e.g., Tkinter or Streamlit), allowing users to upload retinal fundus images and receive diagnostic feedback.

V RESULTS

Output Discussion

The project titled "Diabetic Retinopathy Detection using Deep Learning" successfully demonstrates the automatic identification of diabetic retinopathy (DR) stages from retinal fundus images. The developed system uses a Convolutional Neural Network (CNN) to process and classify input images into categories such as No DR, Mild, Moderate, Severe, and Proliferative DR.

The output is presented through an interactive graphical interface that allows users (such as doctors or researchers) to upload retinal images and receive diagnostic predictions along with visual feedback.

Home Page

The Home Page serves as the entry point of the application. It introduces the purpose of the system—automated detection of diabetic retinopathy—and guides users to key features. It includes navigation links to the Guide, Analyse Fundus, and Contact pages, along with brief project information and login/register options. The layout

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is intuitive, making it easy for first-time users to understand the application's goal.

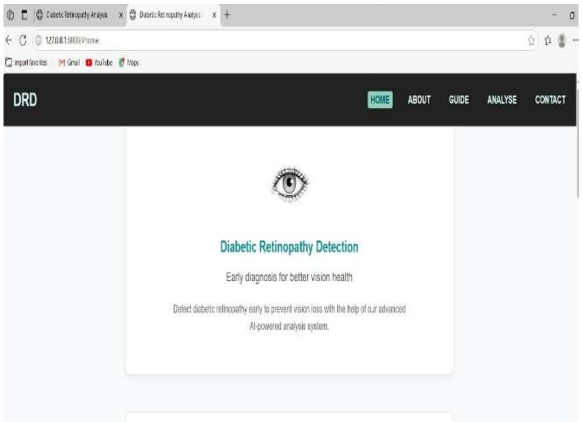

Fig 3: Login Page

Guide Page

The Guide Page provides a clear, step-by-step instruction on how to use the diabetic retinopathy detection system. It guides users through capturing or uploading a retinal fundus image, emphasizing the need for clear and centered images to ensure accurate analysis. Users are then instructed to enter relevant patient details such as name, age, and medical history before submitting the image for analysis. The system processes the input and generates a detailed report that includes the diagnosis, confidence score, and visual highlights of affected areas. This page is designed to make the process straightforward and accessible, ensuring that users can easily navigate from image capture to receiving a comprehensive diagnostic report.

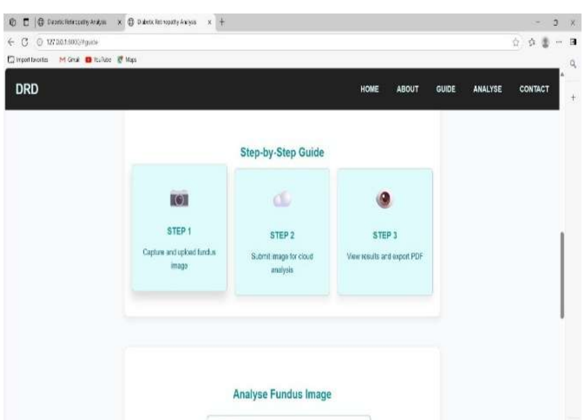

Fig 4: Guide Page

Analyse page

The Analyse Fundus Page serves as the main interface for users to submit their information and retinal fundus images for diabetic retinopathy detection. It prompts users to enter essential details such as name, phone number, and gender, alongside uploading a clear fundus image. Once the data is submitted, the system processes the image using the trained model to detect the presence and severity of diabetic retinopathy. The results are then presented in a detailed report format, highlighting the diagnosis and providing actionable insights. This page ensures that both user information and medical data are collected accurately to generate a personalized and comprehensive analysis report.

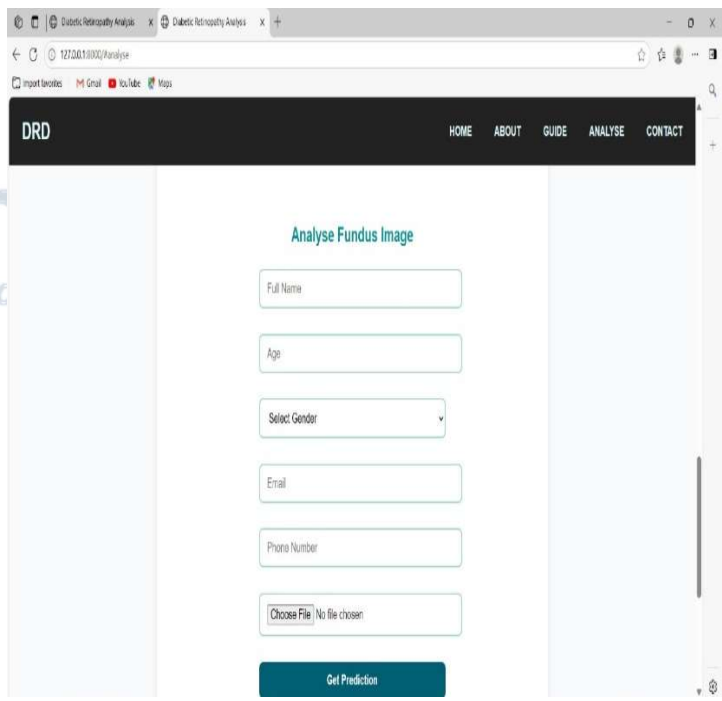

Fig 5: Analyse Page

Contact Page

The Contact Page provides users with a way to reach the developers or medical professionals behind the system. It includes contact forms, email addresses, and possibly links to affiliated institutions. This fosters trust and enables feedback, bug reports, or queries regarding medical accuracy.

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Contact

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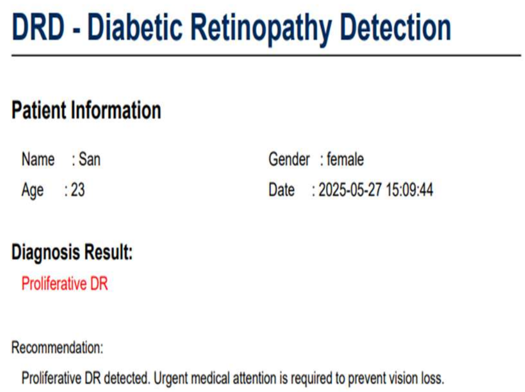
Fig 6: Contact Page

Output Report

- The system generates a comprehensive report based on the user's fundus image and personal details (name, phone, gender).
- It classifies the diabetic retinopathy severity level, from no DR to advanced stages, along with a confidence score.
- The report highlights detected retinal features such as microaneurysms, hemorrhages, and exudates.
- Provides personalized recommendations for follow-up, such as regular screenings or specialist referral.
- Includes disclaimers stating that the report is for screening purposes only and not a substitute for professional diagnosis.
- Allows users to download or print the report in PDF format for easy sharing with healthcare providers.
- Ensures data privacy by securely handling personal and medical information.
- Designed to be user-friendly and easy to understand for both patients and healthcare professionals.
- Optionally, the report can include visual aids like annotated fundus images highlighting affected areas.


DRD - Diabetic Retinopathy Detection

Patient Information

Name : San
Gender : female
Age : 23
Date : 2025-05-27 15:09:44

Diagnosis Result:
Proliferative DR

Recommendation:
Proliferative DR detected. Urgent medical attention is required to prevent vision loss.

Fig 7: PDF Report

VI CONCLUSION

The aims of Diabetic Retinopathy Detection system successfully demonstrates the use of deep learning techniques to classify retinal fundus images into different stages of diabetic retinopathy. The system provides an accurate, efficient, and accessible tool for early screening, helping to identify patients at risk and facilitating timely medical intervention. By integrating user-friendly interfaces and automated analysis, the project bridges the gap between complex medical diagnostics and practical applications. Overall, the system highlights the potential of AI-driven solutions in improving healthcare outcomes and supporting ophthalmologists in managing diabetic eye diseases.

VII.FUTURE ENHANCEMENTS

- Integration of Multi-modal Data: Incorporate additional clinical data such as patient history and blood sugar levels for more comprehensive diagnosis.

- Real-time Image Capture: Add support for direct fundus camera integration for instant image analysis without manual uploads.

- Mobile Application Development: Create a mobile version for wider accessibility, especially in remote or underserved areas.

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- Improved Model Accuracy: Continuously retrain the model with larger and more diverse datasets to enhance classification precision.
- Explainability Features: Implement model interpretability tools to visually explain the AI's decision-making process to users and clinicians.
- Multi-disease Detection: Extend the system to detect other retinal diseases such as glaucoma or age-related macular degeneration.
- Cloud Integration: Enable cloud storage and processing for scalable, secure, and collaborative use.
- User Feedback System: Incorporate feedback mechanisms for users to report issues or suggest improvements, facilitating iterative development.

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