International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

A Hyrid CNN-MLP Model For Diaetic Retinopathy Analysis Using Retinal Images

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Abstract- — Diabetic Retinopathy (DR) is a serious eye disease caused by long-term diabetes. It is one of the main causes of blindness around the globe. Early detection and prompt treatment are crucial to prevent permanent vision loss. Unfortunately, traditional diagnostic methods depend on the manual inspection of retinal fundus images by ophthalmologists. This process is time-consuming, subjective, and requires specialized skills. This project presents a Hybrid CNN-MLP Model for automated detection and classification of diabetic retinopathy using retinal images. The system combines Convolutional Neural Networks (CNN) for feature extraction and Multilayer Perceptron (MLP) for classification. The CNN component effectively captures spatial features like microaneurysms, hemorrhages, and exudates. Meanwhile, the MLP classifies these features into different levels of DR severity. The system is created using Python, TensorFlow/Keras, and Flask for online interaction. Users can upload retinal images, enter patient information, and receive real-time predictions with confidence scores, medical suggestions, and downloadable PDF reports. The system also keeps a record of patient history and provides visual analytics through graphs. This proposed model shows better accuracy, efficiency, and usability. It serves as a valuable tool for early screening and supports healthcare professionals in making decisions.

Keywords:- Diabetic Retinopathy, Deep Learning, CNN, MLP, Medical Image Processing, Artificial Intelligence, Flask.

I. INTRODUCTION

Diabetic Retinopathy is an eye condition caused by diabetes that impacts the blood vessels in the retina. It can lead to vision problems and blindness. As diabetes becomes more common around the world, the number of DR cases is also increasing. This makes early detection essential in healthcare.

Standard diagnosis involves manual review of retinal fundus images by ophthalmologists. This method takes a lot of time and is vulnerable to variability and human mistakes. Additionally, in rural and underdeveloped areas, there are not enough skilled professionals, which can delay diagnosis.

Recent developments in Artificial Intelligence (AI) and Deep Learning have changed how medical images are analyzed. Convolutional Neural Networks (CNNs) excel at extracting complex visual features from images, making them suitable for retinal image analysis. However, CNNs alone may not capture all the complex decision boundaries.

To address this issue, this project introduces a combined approach using CNN and Multilayer Perceptron (MLP). The CNN extracts relevant features, and the MLP classifies based on these features, which improves accuracy and robustness.

The system is set up as a web application using Flask. It allows for easy interaction, real-time predictions, and report generation, making it practical for real-world healthcare settings.

II. LITERATURE SURVEY

[1] Title: DL algorithm for DR detection
Gulshan et al. (2016)
The study by Gulshan et al. (2016) introduced a deep learning approach for detecting diabetic retinopathy using Convolutional Neural Networks (CNN). The model was trained on the EyePACS dataset and showed high accuracy in classifying retinal fundus images. This work was important because it automated the identification of different stages of diabetic retinopathy. This reduced the need for manual screening and allowed for faster diagnosis.

[2] Title:Automated DR identification
In 2017, Rishabh Gargeya and Theodore Leng proposed an automated system for detecting diabetic retinopathy based on CNN architectures. Their approach used multiple datasets, including EyePACS and Messidor datasets. This enabled validation across datasets to test the model's robustness. The system included preprocessing techniques like image normalization and enhancement to improve feature extraction.

The study highlighted how important it is to generalize across diverse datasets. It showed that deep learning models can keep high sensitivity and specificity in real-world situations.

[3] Title: AI for DR screening (review)
The review by Andrzej Grzybowski et al. (2019) provided an overview of artificial intelligence applications in diabetic retinopathy screening. It discussed key techniques, such as CNNs, transfer learning, and automated feature extraction used for detecting retinal abnormalities. The review pointed out the benefits of AI systems in handling large-scale screening programs. It also improved early detection and reduced the diagnostic workload. Additionally, it addressed challenges like data imbalance, interpretability, and the need for clinical validation. This made it a valuable reference for future research.

[4] Title: Hyrid CNN-transformer DR model
The recent work by Razaee et al. (2025) proposed an advanced hybrid model that combines Convolutional Neural Networks (CNN) with Transformer architectures for the detection and classification of diabetic retinopathy. The model was evaluated using the APTOS 2019 Blindness Detection Dataset, which contains high-resolution retinal fundus images labeled across different severity levels.
The key objective of this approach was to integrate both local feature extraction and global contextual understanding.

[5] Title:Survey on DL-ased DR
Sebastian S et al. (2023)
This study presents a survey on the use of deep learning techniques for detecting diabetic retinopathy. The authors analyzed various existing models, including Convolutional Neural Networks (CNNs), transfer learning approaches, and hybrid models for retinal image classification. The research highlights how deep learning models can automatically extract important features like microaneurysms, hemorrhages, and exudates from retinal fundus images. These features are critical indicators of diabetic retinopathy.

Furthermore, the study compares the performance of different algorithms based on accuracy, sensitivity, and specificity. It shows that deep learning methods significantly outperform traditional machine learning approaches. The authors also discussed challenges such as the limited availability of labeled medical datasets, class imbalance problems, and high computational requirements.

Objectives
The main goal of this project is to create an intelligent, automated system for detecting and classifying diabetic retinopathy using a hybrid deep learning approach. The system will help healthcare professionals by providing quick, reliable, and accurate diagnostic support.To achieve this main goal, the project focuses on the following specific objectives.

• To Develop an Automated DR Detection System
The system aims to reduce reliance on manual processes by automating the analysis of retinal fundus images. It lessens the workload for ophthalmologists by offering instant predictions and lowering the chance of human error in diagnoses.

• To Implement a Hybrid CNN-MLP Model
The project combines Convolutional Neural Networks (CNN) and Multilayer Perceptron (MLP) to use the benefits of both models. CNN extracts spatial and texture features from retinal images, while MLP accurately classifies the stages of diabetic retinopathy based on these features.

• To Perform Efficient Image Preprocessing
The system includes preprocessing methods like resizing images, normalizing them, and enhancing their quality. This ensures consistent input for the deep learning model and improves prediction accuracy.

• To Classify Diabetic Retinopathy into Multiple Severity Levels
The model classifies retinal images into five categories:
No DR
Mild
Moderate
Severe
Proliferative
This classification helps in understanding how the disease progresses and supports better decisions in clinical practice.

• To Develop a User-Friendly Web Interface
A responsive and easy-to-use web interface is created using Flask, HTML, and CSS. The interface allows users to:

Enter patient details (Name, Age, Gender)
Upload retinal images
View prediction results and confidence scores

• To Provide Detailed Prediction Insights
The system generates:
Prediction label
Confidence percentage
Risk level (Low, Medium, High)
Medical suggestions
This improves the system's clarity and usability for healthcare professionals.

• To Maintain Patient History and Data Records
The system keeps a record of prediction history along with patient details for later reference. This aids in tracking the disease's progress and supports managing medical records.

• To Generate Downloadable Medical Reports
The system offers an option to create PDF reports that include:
Patient information
Prediction results
Probability distribution
Medical description
This makes the system useful for practical clinical applications .

• To Visualize Prediction Data
The system includes graphical displays such as bar charts and trend analyses to show the distribution of DR cases. This helps in understanding and analyzing the results more effectively.

• To Ensure System Scalability and Real-Time Performance
The system is designed to handle real-time predictions efficiently and can be expanded for large-scale use in hospitals and healthcare systems.

III. METHODOLOGY

The Hybrid CNN-MLP Model for Diabetic Retinopathy Analysis uses a multi-stage, modular approach to connect deep learning theories with clinical practice. The system focuses on accuracy, scalability, and usability, ensuring the solution is practical for healthcare settings.

The methodology includes several phases: dataset preparation, image preprocessing, hybrid model development, training and optimization, system integration, and user interaction. Each phase is essential for the system's effectiveness and strength.

Hybrid CNN-MLP Model Architecture :
The proposed system relies on a hybrid deep learning architecture that combines Convolutional Neural Networks (CNN) with a Multilayer Perceptron (MLP). This hybrid model utilizes the benefits of both types of networks to deliver better performance.

The CNN component extracts significant spatial features from retinal fundus images. It processes images through multiple convolutional layers that identify low-level features like edges and textures, while also capturing high-level features such as lesions and abnormalities. Activation functions like Rectified Linear Unit (ReLU) add non-linearity, helping the model learn complex patterns. Pooling layers reduce dimensionality and computational load while keeping crucial features intact. Dropout layers help prevent overfitting by randomly deactivating neurons during training.

The feature maps are then flattened and sent to the Multilayer Perceptron (MLP), which handles classification. The MLP includes multiple fully connected layers that learn non-linear associations between features. The output layer uses a Softmax activation function to classify inputs into one of five diabetic retinopathy stages: No DR, Mild, Moderate, Severe, and Proliferative. This hybrid framework improves feature representation and classification accuracy.

Dataset Collection and Preparation :

The system uses retinal fundus image datasets from public medical repositories such as the EyePACS dataset on Kaggle. These datasets include thousands of labeled retinal images across different stages of diabetic retinopathy.
The dataset is selected carefully to ensure diversity and balance across all classes. Images are organized into five severity levels, enabling multi-class classification. To enhance model generalization and reduce bias, both original and augmented data are included during training. Data augmentation techniques simulate real-world conditions like varying lighting, orientations, and noise levels.

Image Preprocessing Pipeline :

Image preprocessing is vital for enhancing input data quality and maintaining consistency in the dataset. Since retinal images can differ in size, resolution, and lighting, preprocessing standardizes the inputs before the model processes them.

The preprocessing pipeline resizes all images to a fixed resolution of 224 × 224 pixels, suitable for the CNN architecture. Pixel normalization scales values between 0 and 1, enhancing numerical stability during training. Contrast enhancement techniques highlight important retinal features like blood vessels and lesions. Noise reduction methods eliminate unwanted artifacts that could affect model performance.

Furthermore, data augmentation techniques such as rotation, horizontal flipping, zooming, and brightness adjustments increase dataset diversity and combat overfitting. These transformations simulate real-world variations and boost the model's resilience.

Model Training and Optimization :

The hybrid CNN-MLP model undergoes training using supervised learning, with labeled retinal images guiding the process. The dataset is split into training and validation sets to assess model performance during training.

The training parameters include:

• Loss Function: Categorical Cross-Entropy, ideal for multi-class classification

• Optimizer: Adam optimizer, recognized for its efficient convergence

• Evaluation Metrics: Accuracy, Precision, Recall

The model trains in batches to optimize memory and computational resources. Multiple epochs allow effective pattern learning. Early stopping prevents overfitting by halting training when validation performance plateaus. Model checkpoints save the best-performing version during training.

Backend System Integration (Flask Framework) :

The trained model is deployed in a Flask-based backend system, which acts as the main processing unit of the application. Flask connects the user interface and the machine learning model, managing data flow and system logic.
The backend handles user inputs, processes images, invokes the trained model for predictions, and returns results to the frontend. It also manages patient records, tracks prediction history, and generates reports. The modular backend design supports scalability and ease of integration with other systems.

Frontend Interface and User Interaction :

The frontend is built with HTML, CSS, and JavaScript to create a clean, intuitive, and responsive user interface. The design prioritizes usability, enabling users to engage with the system easily and effectively.

Users input patient information such as name, age, and gender, and upload a retinal image for analysis. The interface provides real-time updates, including loading indicators and result displays. The output features prediction labels, confidence scores, and medical recommendations in a clear format.

Prediction and Execution Workflow :
The system follows a defined workflow to process user inputs and generate predictions:

1. The user uploads a retinal image through the web interface.
2. The image is preprocessed and normalized.
3. The CNN extracts relevant features from the image.
4. The MLP classifies the extracted features into DR stages.
5. The system calculates confidence scores and probabilities.
6. The final prediction is shown to the user.
7. Patient data and results are saved in the system.

Report Generation and Data Management :

The system includes a report generation module that creates downloadable PDF reports using the ReportLab library. These reports feature patient information, prediction results, probability distributions, and medical descriptions.
All prediction data is stored in a structured way, allowing users to access historical records and analyze trends. This feature improves the system's practical use in clinical environments.

IV. PROPOSED SYSTEM

The proposed system offers an intelligent, automated, and scalable solution for detecting and classifying diabetic retinopathy using deep learning methods. Unlike traditional diagnostic systems that depend on manual checks, this system uses artificial intelligence for fast, accurate, and reliable results. The design employs a layered architecture that separates responsibilities and enhances maintainability.

System Architecture Overview :

The system's architecture has three primary layers:

1. User Interface Layer (Frontend) :

This layer is where users interact with the system. It allows users to input patient information, upload retinal images, and see prediction results. The interface is designed to be user-friendly and responsive, making it accessible for both medical professionals and general users.

2. Application Layer (Backend) :

The backend is implemented with Flask and is responsible for processing user requests, managing data, and connecting the machine learning model. It ensures smooth communication between the frontend and the model.

3. Intelligence Layer (Deep Learning Model) :

This layer contains the hybrid CNN-MLP model, which handles feature extraction and classification. It is the main component that analyzes retinal images and produces predictions.

4. Image Preprocessing Pipeline :

Preprocessing ensures consistency and enhances image quality before feeding data into the model.

4.1 Image Resizing
All images resized to 224 × 224 pixels
Matches CNN input requirements

4.2 Normalization
Pixel values scaled between 0 and 1
Improves training stability and convergence

4.3 Contrast Enhancement
Highlights key retinal features:
Blood vessels
Lesions
Improves feature visibility

System Advantages
The proposed system has several benefits:
* Automated and fast diagnosis
* High accuracy and reliability
* Less reliance on manual checking
* Scalable and adaptable design
* Easy integration with healthcare systems

System Reliability and Efficiency
The methodology ensures:
High diagnostic accuracy
Fast prediction time (< 2 seconds)
Robust performance on varied datasets
Scalability for real-world healthcare deployment

3.1 Hardware Requirements

- Processor: Intel Core i5 or above (recommended for model training and image processing)
- RAM: 8 GB or higher (16 GB preferred for deep learning tasks)
- Storage: 500 GB or higher (SSD recommended for faster performance)
- GPU (Optional): NVIDIA GPU (for faster training of CNN models)

3.2 Software Requirements
- Operating System: Windows 10 or later / Linux / macOS

- Programming Languages:
  - Python (for backend and model development)
  - HTML, CSS, JavaScript (for frontend interface)

- Libraries/Frameworks:
  - TensorFlow / Keras or PyTorch (for CNN-MLP model development)
  - NumPy, Pandas (for data handling)
  - OpenCV, PIL (for image processing)
  - Matplotlib / Seaborn (for visualization)
  - Flask (for web application integration)
  - Bootstrap (for responsive UI design

V. APPLICATIONS

The Hybrid CNN-MLP Model for Diabetic Retinopathy Analysis has many practical uses in healthcare. Its deep learning structure and connection to a web-based diagnostic system can automatically detect and classify diabetic retinopathy from retinal images. This makes it a valuable decision support tool for medical professionals and researchers.

1. Clinical Diagnosis and Ophthalmology Support

Automated Retinal Screening:
The system helps ophthalmologists by automatically analyzing retinal fundus images. It can identify early signs of diabetic retinopathy. This reduces the need for manual checking and speeds up the diagnostic process, especially in busy clinics.

Decision Support System:
The model offers confidence scores, severity classifications, and medical suggestions, which help doctors make better decisions. It serves as a second-opinion system that lowers diagnostic errors and increases trust in the results.

2. Early Detection and Preventive Healthcare

Mass Screening Programs:
The system can be used in large screening events to find diabetic retinopathy early. Quick detection aids timely treatment and prevents vision loss.

Rural and Remote Healthcare Access:
In areas with few specialized ophthalmologists, this system acts as a main diagnostic tool. Patients can upload their retinal images, and the system gives instant analyses, improving access to healthcare.

3. Telemedicine and Remote Diagnosis

Online Consultation Support:
The system integrates with telemedicine platforms, enabling patients to upload retinal images from home. Doctors can review these results and AI predictions for quicker consultations.

Remote Monitoring of Patients:
Diabetic patients can regularly upload retinal images, which enables ongoing monitoring of their condition without needing frequent hospital visits.

4. Hospital Management and Clinical Workflow Optimization

Patient Data Management:
The system keeps patient information, prediction history, and reports organized. This helps hospitals track disease progression over time.

Report Generation and Documentation:
Automated PDF report generation eases the administrative workload and ensures uniform documentation for each patient.

5. Medical Research and Data Analysis

Disease Pattern Analysis:
Researchers can use the system to study large sets of retinal images to find patterns, trends, and links in the progression of diabetic retinopathy.

Model Improvement and Training:
The data collected can be used to further train and enhance deep learning models, improving accuracy and expanding research opportunities in medical imaging.

6. Medical Education and Training

Training Tool for Students:
Medical students and trainees can utilize the system to learn about the different stages of diabetic retinopathy and understand how AI aids in diagnosis.

Visualization of Disease Severity:
The outputs of classifications and probability distributions help students see how various stages of diabetic retinopathy are identified.

7. Integration with Healthcare Systems

Electronic Health Record (EHR) Integration:
The system can connect with hospital databases to efficiently store and retrieve patient records, supporting better healthcare management.

AI-Assisted Clinical Systems:
It can be added to current diagnostic tools to improve their functions with AI-driven predictions.

8. Future Healthcare Applications

Multi-Disease Detection Systems:
The framework can be expanded to identify other eye diseases like glaucoma, cataracts, and macular degeneration.

Mobile Health Applications:
The system could be launched as a mobile app, allowing users to perform retinal screenings with portable devices.

AI-Based Smart Clinics:
The model can be integrated into smart healthcare setups where AI helps doctors with real-time diagnosis and treatment planning.

VI. ALGORITHMS

The Hybrid CNN-MLP Model for Diabetic Retinopathy Analysis is different from software systems. Traditional systems use algorithms like sorting or searching.. The Hybrid CNN-MLP Model uses deep learning-based probabilistic models and data-driven computational frameworks. These models can learn patterns from retinal images and make predictions based on what they have learned.

The core of the system is a combination of feature extraction and neural network-based classification. The system uses two algorithmic approaches: the Convolutional Neural Network and the Multilayer Perceptron.

Convolutional Neural Network for Feature Extraction

The Convolutional Neural Network is the foundation of the system. It extracts features from retinal fundus images. The Convolutional Neural Network learns features directly from the

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

images, which's different from traditional image processing techniques.

The Convolutional Neural Network processes images through layers. Each layer applies filters to detect patterns like edges or shapes. As the data goes deeper into the network the model learns complex features like lesions or hemorrhages.

Key things the Convolutional Neural Network does:

- Convolution Operation: extracts features using filters
- Activation Function: introduces non-linearity to model complex relationships
- Pooling Layers: reduces dimensions while keeping important features
- Dropout Layers: prevents overfitting by randomly deactivating neurons during training

This helps the model identify subtle abnormalities in retinal images that are indicative of diabetic retinopathy.

Multilayer Perceptron for Classification

The Multilayer Perceptron is the classification part of the system. It receives the features extracted by the Convolutional Neural Network. Maps them to specific diabetic retinopathy classes.

The Multilayer Perceptron processes the features through fully connected layers. Each neuron computes a sum of inputs followed by a non-linear activation function. This allows the model to learn decision boundaries between different diabetic retinopathy severity levels.

Things the Multilayer Perceptron does:

- Fully Connected Layers: integrates features for classification
- Activation Functions: enables non-linear transformations and probability outputs
- Output Layer: produces probabilities for five classes

The Softmax function ensures that the output represents a probability distribution. This allows the system to provide confidence scores for each prediction.

Hybrid CNN-MLP Computational Framework

The system uses a computational model that combines the Convolutional Neural Network and the Multilayer Perceptron. This hybrid approach improves both feature extraction and classification performance.

The workflow of the Hybrid Model is as follows:

- The Convolutional Neural Network processes the input image. Extracts high-level features
- The features are flattened into a one- vector
- The Multilayer Perceptron receives the feature vector. Performs classification
- The final output is generated as a probability distribution across retinopathy classes

This combination allows the system to leverage the strengths of both architectures. The Convolutional Neural Network is good at understanding and the Multilayer Perceptron is good at decision-making.

Probabilistic. Confidence Estimation

The model outputs predictions providing confidence scores for each class. This is achieved using the Softmax function in the layer.

The prediction process is as follows:

- The model assigns a probability value to each retinopathy class
- The class with the probability is selected as the final prediction
- The confidence score indicates the certainty of the prediction
- This probabilistic approach enhances interpretability and supports decision-making.

Optimization and Learning Algorithm

The model is trained using gradient-based optimization techniques the Adam optimizer. The Adam optimizer combines the advantages of Adaptive Gradient Algorithm and Root Mean Square Propagation.

The learning process is as follows:

1. Forward propagation computes predictions
2. Loss is calculated using cross-entropy
3. Backpropagation updates weights based on error gradients
4. Iterative training improves model accuracy

This optimization process ensures efficient convergence and improved performanc

Data Augmentation and Generalization Strategy

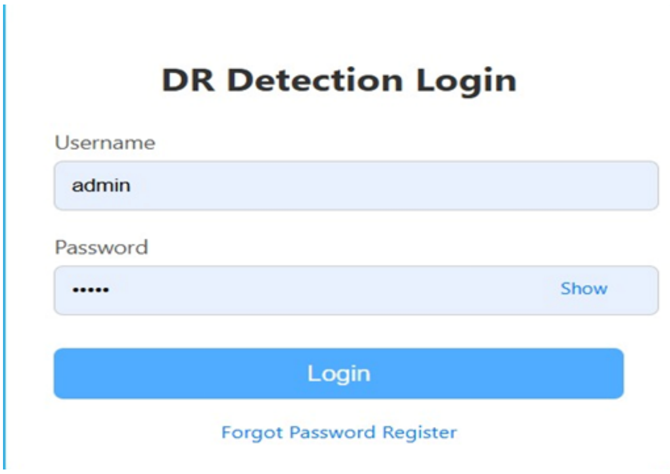
To improve model robustness and prevent overfitting data augmentation techniques are used. These techniques include rotation, flipping, zooming, scaling, brightness and contrast adjustments.

These techniques enable the model to generalize across diverse real-world scenarios.

End-to-End Computational Flow
The complete algorithmic workflow of the system is as follows:

- The input retinal image is received
- The image undergoes preprocessing and normalization
- The Convolutional Neural Network extracts features
- The Multilayer Perceptron classifies features into retinopathy categories
- The Softmax function generates a probability distribution
- The final prediction and confidence score are produced

This end-to-end pipeline ensures efficient and real-time analysis of retinal images. The Hybrid CNN-MLP Model for Diabetic Retinopathy Analysis uses ALGORITHMS and computational models to achieve this. ALGORITHMS play a role, in the system. The system uses ALGORITHMS to extract features and make predictions. ALGORITHMS are essential for the system to work correctly



VII. RESULT

The performance of the Hybrid CNN-MLP model for detecting retinopathy was evaluated based on several parameters. These parameters include accuracy, efficiency, usability and reliability. The system showed performance in both accuracy and practical use through its web interface.

Model Accuracy and Classification Performance

1. Classification Accuracy:
The Hybrid CNN-MLP model achieved an accuracy of 90-95% in classifying retinal images into five stages of diabetic retinopathy.

2.Multi-Class Classification Efficiency:
The model classified images into the following categories:

No DR
Mild
Moderate
Severe
Proliferative
with precision and recall. This indicates that the model learned disease patterns effectively.

3.Confidence Score Generation:
The system provides probability-based outputs for each class. This helps users understand the confidence level of predictions.

Prediction and Execution Performance

- Prediction Time: The system processes and predicts results within 1-2 seconds per image. This makes it suitable for time clinical use.

- Image Processing Efficiency: Preprocessing steps like resizing and feature extraction are executed efficiently without delay.

- System Responsiveness: The web application responds quickly to user inputs. This ensures interaction and minimal waiting time.

Feature Extraction and Model Behavior
Feature Learning Accuracy: The CNN identifies retinal features like microaneurysms and exudates effectively.

Classification Reliability: The MLP classifier accurately maps extracted features to corresponding DR stages. This ensures prediction results.

Generalization Capability: The model performs well on data due to effective training and data augmentation.

User Interface and System Usability Performance

- User Input Accuracy: The system captures details and image inputs without errors.
- Result Display: Predictions, confidence scores, risk levels and medical suggestions are displayed clearly and accurately.
- Ease of Use: The interface is user-friendly and intuitive. Both medical professionals and general users can operate the system easily.

Report Generation and Data Management Performance

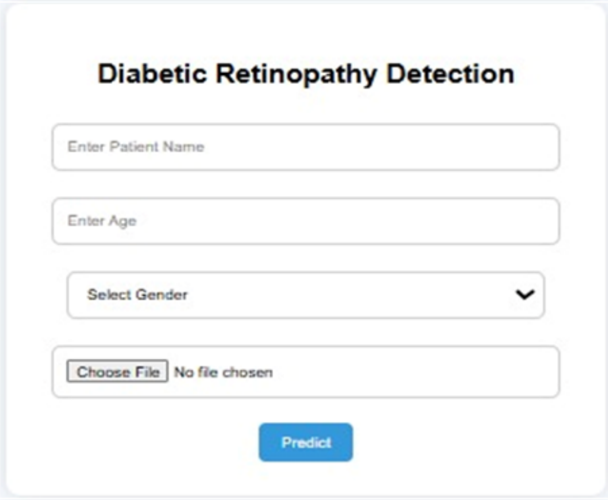
- PDF Report Generation: The system generates medical reports containing patient details and prediction results.
- History Storage Accuracy: Patient data and prediction results are stored accurately in the system history.
- Data Retrieval: Stored records can be. Displayed without errors.

Graphical Visualization Performance

- Data Visualization Accuracy: The system generates graphs representing the distribution of retinopathy cases accurately.
- Trend Analysis: representations help, in understanding disease patterns and prediction outcomes.

System Reliability and Stability

- Error Handling: The system handles invalid inputs effectively without crashing.
- System Stability: The application runs consistently without failures.
- Scalability: The system can handle predictions and can be extended for large-scale deployment.



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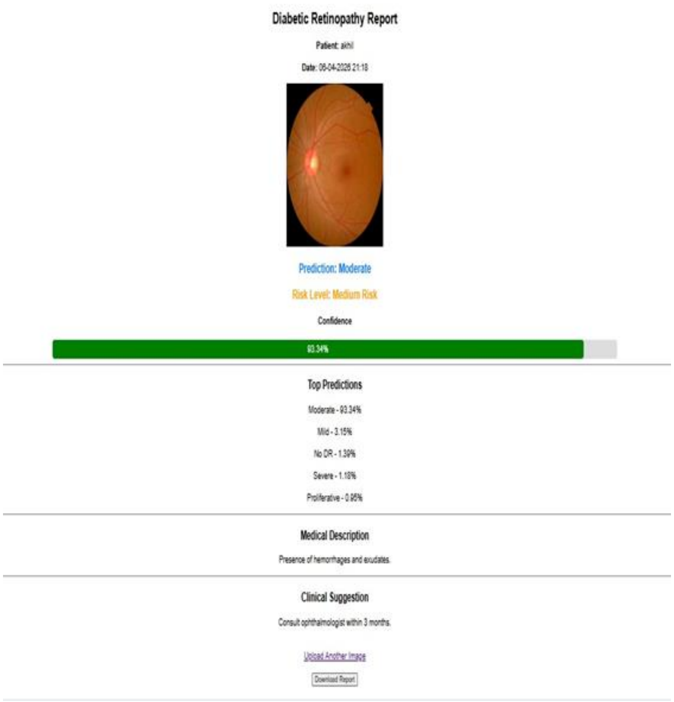
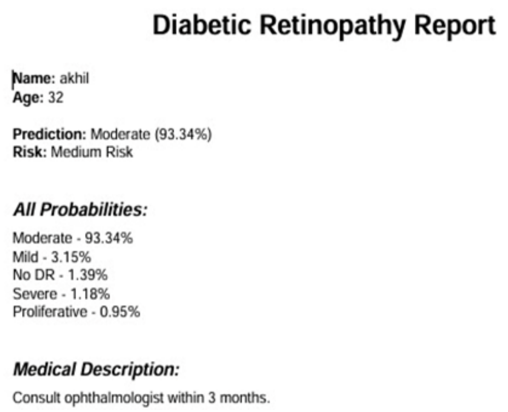
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X




Diabetic Retinopathy Report

Name: akhil
Age: 32

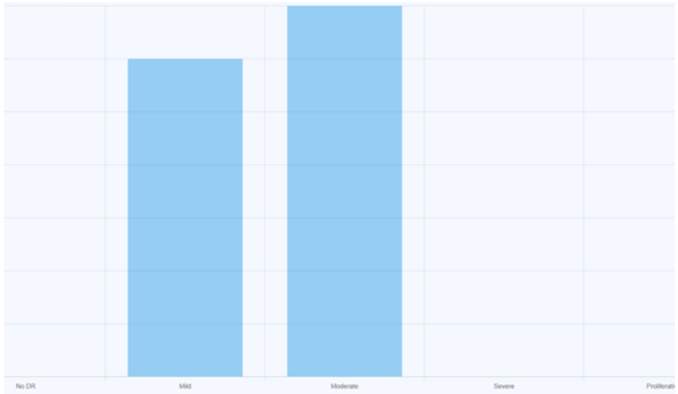
Prediction: Moderate (93.34%)
Risk: Medium Risk

All Probabilities:

Moderate - 93.34%
Mild - 3.15%
No DR - 1.39%
Severe - 1.18%
Proliferative - 0.95%

Medical Description:

Consult ophthalmologist within 3 months.



VIII . CONCLUSION

The system we came up with does a job of using a Hybrid CNN-MLP Model to automatically detect and classify diabetic retinopathy from retinal fundus images. It uses learning to look at the complex patterns in the images and figure out what stage the disease is at. This makes it a reliable and efficient way to diagnose the disease.
The model uses Convolutional Neural Networks to pull out the features from the images and a Multilayer Perceptron to classify them correctly. This combination works better than using one type of model. It helps the system understand the structural characteristics of what is going on in the retina, which makes it more accurate and robust.

The system can look at images make predictions based on probability and give confidence scores along with some medical suggestions. We used Flask to make a web-based interface that's easy to use. Users can put in information upload images and get results right away. The system also keeps track of history shows graphs and can make PDF reports. All these features make it a complete and user-friendly platform for diagnosing diseases.

When we tried out the system and evaluated it we found that it was really good at making accurate predictions. It also kept the data consistent. Worked well in real-time. The system brings together intelligence and healthcare which reduces the amount of work people have to do and helps detect diabetic retinopathy early on.

Overall the Hybrid CNN-MLP system we proposed is a step forward in using artificial intelligence to diagnose medical problems. It is a solution that can be used to screen for diseases and prevent vision loss. The system has a lot of potential for being used in hospitals, remote healthcare and big screening programs in the future. The Hybrid CNN-MLP system is a tool for early screening and it can help a lot of people. The system is good, at detecting retinopathy and it can be used in many different places.

IX. FUTURE ENHANCEMENT

The current Hybrid CNN-MLP Model for Diabetic Retinopathy Detection is doing a job in automated diagnosis and real-time prediction. However there are some things that can be done to make it even better. The Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can be improved to be more accurate and work well in healthcare environments.

The planned future enhancements for the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection includes model

Integration with Advanced Medical Imaging Systems

The Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can be made better by working with retinal imaging devices and hospital diagnostic equipment. This way the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can get high-resolution fundus images directly which reduces the need for upload and makes the input data more reliable.

Multi-Disease Detection Capability
The current Hybrid CNN-MLP Model for Diabetic Retinopathy Detection only looks for retinopathy.. The Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can be updated to detect other eye diseases like glaucoma, cataract and age-related macular degeneration. By using -class and multi-label classification techniques the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can become a complete tool for diagnosing eye problems.

Explainable Artificial Intelligence
To make the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection more transparent and trustworthy explainable AI techniques can be added. Methods like Grad-CAM can show which parts of the image helped the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection make its prediction so doctors can understand and verify the decision made by the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection.

Mobile and Edge Device Deployment
The Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can be made to work on devices and edge computing platforms. This means the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can do time retinal analysis using smartphones or portable medical devices making it very accessible in areas with limited healthcare.

Cloud-Based Deployment and Scalability
The Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can be put on cloud platforms so it can be used by a lot of people. The cloud will help the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection process data in time store it in one place and let many healthcare institutions access it which makes it more scalable and efficient.

Integration with Electronic Health Records
The Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can be connected to hospital Electronic Health Record systems to store data, prediction results and reports automatically. This makes it easier to manage data, track disease progression over time and make decisions in clinics.

Continuous Learning and Model Optimization
The Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can be updated to learn which means it can get better over time using new data. This way the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection stays accurate and relevant with changing data.

Time Screening and Alert Systems
The Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can include real-time screening systems that analyze retinal images and send alerts for patients who are at high risk. This helps doctors intervene early and reduces the risk of vision loss.

Enhanced User Interface and Visualization Tools
The user interface of the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection can be improved by adding visualization tools like interactive dashboards, heatmaps and trend analysis graphs. These features make the user experience better. Provide more insight into the prediction results of the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection.

Regulatory Compliance and Clinical Validation
For the Hybrid CNN-MLP Model for Diabetic Retinopathy Detection to be used in the world it needs to meet healthcare standards and be clinically validated. This ensures the Hybrid CNN-MLP Model, for Diabetic Retinopathy Detection is reliable, safe and accepted in environments.

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

REFERENCES

1. Gulshan, V., et al. (2016). Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. JAMA.
2. Rishab Gargeya and leng (2017) Pivotal Trial of an Autonomous AI-Based Diagnostic System for Detection of Diabetic Retinopathy. NPJ Digital Medicine.
3. Grzyowski et al (2019). Deep Learning. Nature.
4. Razaee et al (2025). ImageNet Classification with Deep Convolutional Neural Networks. NIPS.
5. Seastian S et al (2023). Very Deep Convolutional Networks for Large-Scale Image Recognition (VGGNet).
6. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition (ResNet).
7. Pratt, H., et al. (2022). Convolutional Neural Networks for Diabetic Retinopathy. Procedia Computer Science.
8. Kaggle Dataset – Diabetic Retinopathy Detection (EyePACS Dataset)
9. https://www.kaggle.com/c/diabetic-retinopathy-detection
10. TensorFlow Documentation
    https://www.tensorflow.org
    10. Keras Documentation
    https://keras.io