IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Advanced Classification Technique For Diabetic Eye Disorders

[1]Krishna Gudi, [2]A Ramyasree, [3]Charishma M, [4]Harshitha S, [5]Harshitha S

[1]Associate Professor, [2]Student, [3]Student, [4]Student,[5]Student

Department of Computer Science

K. S. Institute of Technology Bangalore, India

Abstract: This project develops an AI system to detect and classify diabetic eye diseases early using retinal images. It uses image enhancement and CNNs to extract key features. A hybrid model combining deep learning and traditional ML classifies disease types and stages. The system is trained on public datasets and considers patient info like age. It achieves high accuracy in identifying conditions like diabetic retinopathy and glaucoma. This tool helps doctors with faster, more accurate diagnosis and supports telemedicine use.

I. INTRODUCTION

Vision is one of the most vital human senses, contributing to nearly 80% of the information we perceive preventing conditions such as diabetic retinopathy, glaucoma, and cataracts—three of the most common causes of vision loss globally. While some eye issues are minor and can resolve on their own, others require timely medical intervention to prevent long-term damage. Early diagnosis plays a key role in managing these conditions effectively.

This project focuses on the use of Artificial Intelligence (AI) and Deep Learning (DL) technologies for the early detection and classification of major eye diseases. By analysing fundus images and patient data, the system can identify visual symptoms associated with diabetic eye syndrome, glaucoma, and cataracts. A combination of image processing techniques, neural network models, and machine learning algorithms is used to improve accuracy and reliability.

.

The model considers various patient factors—such as age, medical history, and clinical indicators—to enhance diagnostic precision. Through image recognition and data mining, the system can efficiently detect and localize eye-related abnormalities. The study also explores the integration of DL in real-world clinical screening systems and addresses the current limitations in deploying these technologies.

Ultimately, the goal is to build a robust, AI-powered screening solution that supports health professionals, improves diagnostic outcomes, and helps prevent vision impairment by enabling early treatment. This project highlights how AI can transform traditional eye disease screening into a faster, more accessible, and cost-effective process.

This paper represents the development, implementation of an intelligent system designed for the automatic detection and classification of diabetic eye diseases using retinal (fundus) images. The primary focus is on identifying conditions such as diabetic retinopathy, glaucoma, and cataracts, which are among the leading causes of vision impairment globally.

The system is trained and validated on publicly available datasets of annotated fundus images. It demonstrates high accuracy in detecting and classifying diabetic eye disorders. This work highlights the potential of AI in healthcare, especially in early disease detection, where timely intervention can significantly improve patient outcomes.

II. LITERATURE REVIEW

"Deep Learning for Diabetic Retinopathy Detection"
This study [1] investigates the application of deep learning, particularly Convolutional Neural Networks (CNNs), in detecting diabetic retinopathy through retinal images. It highlights the capability of CNNs to recognize intricate patterns in medical imaging data. Building on this concept, our project employs CNN architectures to automatically extract and learn important features from fundus images, enabling precise classification of diabetic eye conditions. This integration ensures that subtle visual indicators are captured effectively, improving early detection accuracy.

"Automated Glaucoma Detection Using Fundus Images"
This research [2] explores machine learning algorithms for glaucoma screening using fundus images, emphasizing the importance of feature selection and preprocessing. Inspired by these findings, our system incorporates a preprocessing stage that enhances image quality and contrast, allowing for better feature extraction. It also uses ML classifiers in combination with deep learning models to boost classification performance and differentiate between various eye diseases.

"Hybrid Deep Learning Systems in Medical Diagnostics"
This study [3] examines hybrid systems that merge deep learning with traditional machine learning methods to improve diagnostic decision-making. It suggests that such systems can provide higher robustness and accuracy. Our project adopts this approach by combining CNN-based feature extraction with ML-based classification modules, resulting in a more efficient and reliable disease classification pipeline.

"AI-Powered-Diagnostics"
This work [4] discusses the current limitations and future potential of AI applications in healthcare, including data quality, interpretability, and real-time deployment. Drawing from these insights, our system focuses on using publicly available, well-annotated datasets for training and testing. It also emphasizes interpretability by mapping results to understandable diagnostic stages, helping medical professionals make informed decisions with AI assistance
.
"Diabetic Retinopathy Classification Using Retinal Lesions"
This paper [5] focuses on lesion-based classification of diabetic retinopathy, stressing the importance of localizing microaneurysms, haemorrhages, and exudates. While our system does not rely solely on lesion segmentation, it benefits from this principle by training the model to recognize these features as part of its feature-learning process, allowing for stage-wise classification and better disease understanding.

"Automated Cataract Detection Using Image Processing"
This research [6] focuses on cataract detection through image processing techniques, using contrast enhancement and edge detection to isolate the cataract region within fundus images. While our system primarily focuses on diabetic eye diseases, we integrate similar image preprocessing steps to enhance the visibility of key features like exudates and microaneurysms in diabetic retinopathy. By borrowing effective image enhancement strategies from cataract detection, we improve the overall quality of the input images, aiding more accurate diagnoses.

"AI-Based Detection of Diabetic Eye Disease"
This review [7] presents a comprehensive overview of various AI and machine learning methods used in diabetic eye disease detection, with a particular focus on diabetic retinopathy. It discusses the challenges of detecting early signs of the disease and the role of automated systems in improving diagnosis efficiency. Drawing from this, our project incorporates state-of-the-art deep learning frameworks, which allow the model to learn from a wide range of retinal features. We also address the challenges highlighted in the review, such as ensuring data diversity and the interpretability of AI models.

"Leveraging Transfer Learning for Medical Image Analysis"
This study [8] explores the use of transfer learning in medical image analysis, particularly for tasks with limited annotated data. It shows that pre-trained deep learning models, fine-tuned for specific medical conditions, can significantly improve model performance. In our work, we implement transfer learning by fine-tuning a pre-trained CNN model on a dataset of diabetic retinopathy images, allowing the system to benefit from general image features learned on large-scale datasets. This approach helps enhance performance when working with smaller datasets, a common challenge in medical imaging.

III SOFTWARE REQUIREMENTS

To ensure the effective development and execution of the proposed system for detecting and classifying diabetic eye diseases, several software components are required. These tools collectively support data preprocessing, model training, image analysis, and result visualization.

Operating System: The system is designed to run on either 64-bit Windows 10 or Ubuntu 20.04 LTS, as both operating systems offer stable environments and broad compatibility with essential machine learning and image processing libraries.

Programming Language: Python (version 3.8 or later) is selected as the core programming language due to its simplicity, readability, and rich ecosystem of libraries specifically tailored for artificial intelligence, data science, and image analysis.

Machine Learning Libraries:
TensorFlow (version 2.4 or later): A powerful open-source platform widely used for building and deploying deep learning models.
Keras : Integrated with TensorFlow, keras provides an easy-to-use API for designing and training neural networks efficiently.
Scikit-Learn: Utilized for traditional machine learning tasks, including classification, model evaluation, and cross-validation.

Data Processing and Visualization Libraries
NumPy: Supports high-speed mathematical operations and handling of multidimensional arrays.
Pandas: Offers robust data structures for managing and analysing large datasets efficiently.
Matplotlib and Seaborn: Used to create informative visualizations, such as distribution plots, heatmaps, and performance metrics, aiding in model interpretation and result presentation.

Image Processing Library
OpenCV: A comprehensive computer vision library employed for handling image-related operations, such as resizing, filtering, contrast adjustment, and noise reduction—crucial steps for preprocessing fundus images before analysis.

Integrated Development Environment (IDE)
PyCharm or Visual Studio Code is recommended for writing, testing, and debugging Python code. These IDEs offer useful features like syntax highlighting, version control integration, and plugin support, improving the development workflow.

IV SYSTEM DESIGN

1. System Architecture

The proposed system adopts a modular and layered architecture optimized for processing medical images and running deep learning models. It ensures efficiency, scalability, and real-time performance. The architecture comprises the following main components:
Image Input Layer:
This layer is responsible for receiving high-quality retinal fundus images from publicly available datasets or clinical uploads. Images are validated for format, resolution, and clarity.

Preprocessing Module:
To ensure consistency and enhance model performance, this module performs operations like resizing, noise reduction, normalization, and contrast enhancement using OpenCV and NumPy.
Deep Learning Model Layer:
At the core lies a Convolutional Neural Network (CNN) built using TensorFlow and keras. This model automatically learns visual features from retinal images and classifies them based on the severity and type of eye disease, such as diabetic retinopathy, glaucoma, or cataracts.
Classification Engine:
Post feature extraction, a hybrid classification system processes the output using a combination of deep learning-based predictions and machine learning techniques (via Scikit-learn) for improved accuracy and interpretability.
Output Interface:
This layer displays results such as disease presence, severity level, and confidence scores. It also supports visualization of feature maps or annotated images for medical professionals.

2. User Interface (UI) Design

Although the primary focus is on backend processing and analysis, a lightweight UI can be integrated for better interaction, especially for clinical settings. Key UI features include:
Upload Interface: Allows users to easily upload fundus images from local devices or connected systems.
Visual Feedback: Displays disease classification results with color-coded indicators and annotated heatmaps.
Diagnostic Logs: Summarizes the analysis with timestamps, prediction confidence, and patient information.
Accessibility Features: Options for high-contrast mode and large-text display support ease of use in various environments.

3. Core Functionalities & Features

Real-Time Disease Detection: The model provides instant feedback after image submission, classifying the disease type and its severity based on trained features.
Automated Image Preprocessing: Enhances image clarity and quality automatically, ensuring better model predictions without manual intervention.
Hybrid Model Design: Combines deep learning for visual recognition with classical ML techniques for better generalization and reduced overfitting.
Model Evaluation Dashboard: Visualizes metrics such as accuracy, precision, recall, and loss graphs, aiding in continuous model improvement and research.
Scalable Deployment: The system can be deployed on cloud platforms or integrated into clinical diagnostic tools, making it adaptable for both research and real-world medical applications.

V METHODOLOGY

Front-End Development Using Python Flask
Modern applications increasingly prioritize user experience by moving away from traditional command-line interfaces. Instead, they adopt interactive Graphical User Interfaces (GUIs), which make software more accessible and intuitive. Through the use of buttons, drop-down menus, input fields, and visual feedback mechanisms, GUIs significantly enhance usability and user engagement.

Flask Web Framework
Flask is a lightweight and flexible Python-based web framework, well-suited for building web applications that are both simple and powerful. It supports modular, object-oriented programming and is particularly useful for integrating interactive elements into a web-based interface. One of Flask's key benefits is its cross-platform compatibility—it functions smoothly on Windows, macOS, and Linux systems. By leveraging system-native styling and components, Flask apps can achieve a familiar and seamless user experience across different environments.

Data Collection and Preprocessing

The image dataset used in this project was sourced from a medical institution specializing in ophthalmology. It comprises a wide variety of retinal fundus images captured under diverse conditions. Differences in camera models, resolutions, lighting conditions, and image quality contributed to the high variability within the dataset. Image resolutions range from 2592 × 1944 to 4752 × 3168 pixels, making uniformity crucial for effective model training.

Hyperparameter Initialization and Model Training

Before constructing the network architecture, key hyperparameters were carefully selected to optimize training efficiency and accuracy. The momentum coefficient (β) was set to 0.9, a standard value that helps stabilize training by accelerating gradients in consistent directions and dampening oscillations.

Image Preprocessing

The original retinal fundus images varied significantly in resolution and aspect ratio. To standardize input data across the network, each image was resized to 256 × 256 pixels. Additionally, green channel extraction was applied since the green spectrum in fundus images tends to highlight features such as microaneurysms and blood vessels more effectively. This preprocessing ensures better feature visibility, especially for key diabetic retinopathy markers like microaneurysms, which appear as small red dots and are among the earliest signs of the disease. Grayscale enhancement was also applied to emphasize these structures during training.

Training Algorithm

For the training phase, the Stochastic Gradient Descent with Momentum (SGDM) algorithm was employed. This optimization method is a refined version of the basic SGD, enhanced with momentum to improve convergence speed and reduce erratic updates caused by noisy gradients. This method smoothens the training trajectory, making it less sensitive to noisy gradients and more directed toward the global minimum. All input images were resized and normalized to fit the requirements of the pretrained architectures. This significantly reduced the training time while improving the overall performance of the network on the diabetic eye disease dataset.

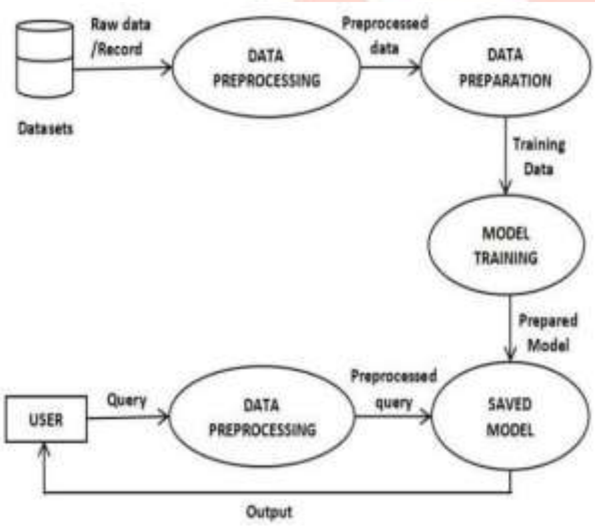

Fig 1 Methodology

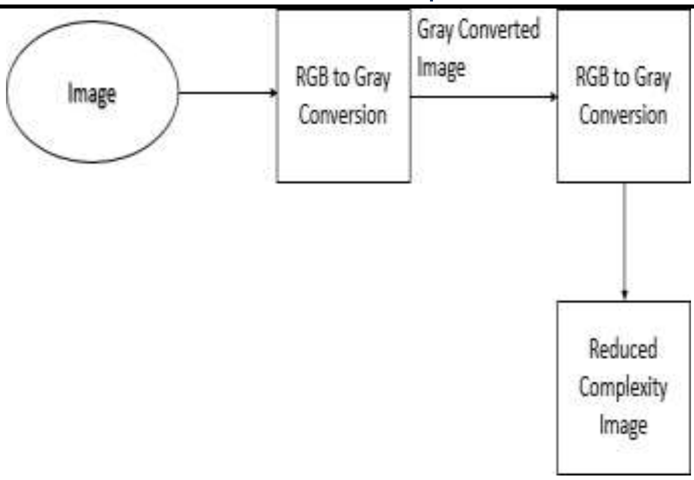

Fig 2 Data Preprocessing

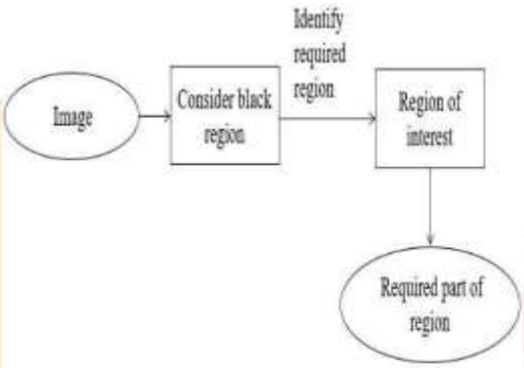

Fig 3 Data Preparation

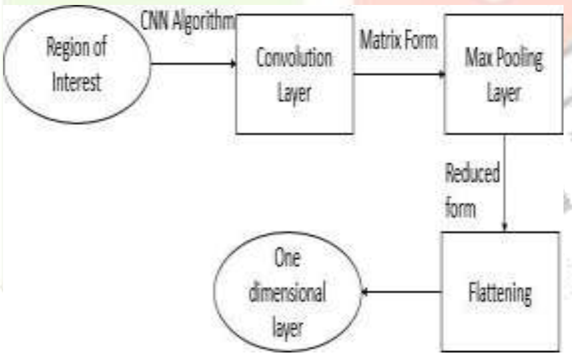

Fig 4 Model Training

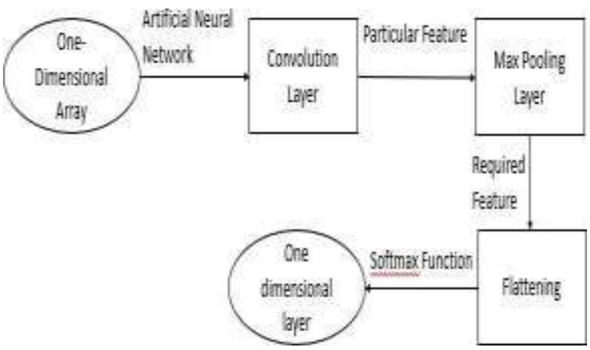

Fig 5 Saved Model

VI IMPLEMENTATION

1. Dataset Collection
Collect retinal fundus images from sources like:
EyePACS, APTOS, Messidor.
Store images in data/raw/ directory.
Create a CSV/Excel file to map each image to a diagnosis label (0–4).

2. Data Preprocessing
Read and resize each image to 224x224 pixels
.Normalize pixel values (divide by 255).
Convert to RGB format if needed.

3. Label Encoding
Encode diagnosis labels:
0: No DR
1: Mild
2: Moderate
3: Severe
4: Proliferative DR

4. Train-Test Split
Split the dataset into:
80% for training
20% for testing

5. Model Building (CNN)
Create a Convolutional Neural Network using TensorFlow/Keras.
Include layers: Conv2D → Max Pooling → Flatten → Dense.

6. Model Compilation and Training

7. Save Trained Model

8. Prediction / Query System

9. Evaluation.

VII RESULT

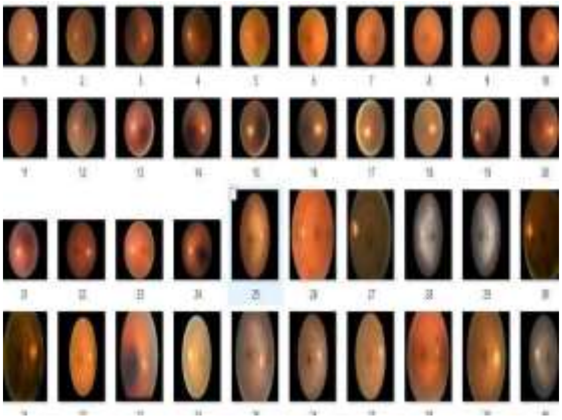

Fig 6 Data Set

Fig 7 User Login Interface for Disease Detection System

Fig 8 Image Upload and Analysis Page for Diabetic Eye Disorder Classification

Fig 9 Diagnosis Result and Remedies Page for Cataract Detection

Eye Disease Diagnosis Report

Patient Name: Charishma M

Patient Name: 18

Status: Proliferate_DR

Accuracy: The predicted image of the normal is with a accuracy of 99.97256398200989%%

Remedies:
Surgery: Surgery is the most effective treatment for cataracts.

Prescription Eyewear: In the early stages of cataracts, prescription eyewear such as glasses or contact lenses may help improve vision.

Eye Drops: Some eye drops may be prescribed to help manage symptoms associated with cataracts, such as dry eyes or discomfort.

Lifestyle Changes: Making certain lifestyle changes can help slow the progression of cataracts or reduce the risk of developing them.

Fig 10 AI Report Generation

VIII CONCLUSION

This project presents a deep learning-based approach for the early detection and classification of diabetic eye diseases using retinal fundus images. By leveraging convolutional neural networks and advanced image preprocessing techniques, the system efficiently identifies visual indicators of conditions like diabetic retinopathy, glaucoma, and cataracts. The integration of both machine learning and deep learning models enhances the accuracy of classification, making it a reliable tool for clinical diagnosis.

The developed model demonstrates promising results on benchmark datasets, showing high precision in distinguishing between various stages of eye disorders. The use of transfer learning, along with effective hyperparameter tuning, contributed to improved training performance and generalization. The system's ability to process and analyse large volumes of medical images with minimal human intervention highlights its potential for real-world medical applications.

IX FUTUTRE SCOPE

In the future, this system can be further developed to support real-time screening in clinical settings and rural healthcare centers by deploying it on portable diagnostic devices or cloud-based platforms. As technology advances, the model can be expanded to detect a wider range of eye disorders beyond diabetic retinopathy, glaucoma, and cataracts, increasing its medical utility. Integration with mobile applications could enable patients and healthcare providers to capture and analyse retinal images instantly, improving accessibility to early diagnosis. Furthermore, incorporating larger and more diverse datasets would enhance the model's accuracy and reduce bias across different populations. Adding explainable AI components could provide transparency into the model’s predictions, supporting better clinical decisions. The system could also be integrated with electronic health records to personalize diagnostics based on a patient’s medical history. Additionally, supporting telemedicine applications would allow specialists to remotely assist in diagnoses, making quality eye care more widely available. With continuous learning capabilities, the model can evolve over time, adapting to new data and improving its performance as new research and clinical guidelines emerge.

REFERENCES

[1] Gulshan, V., Peng, L., Coram, M., et al. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 2402–2410. https://doi.org/10.1001/jama.2016.17216

[2] Pratt, H., Coenen, F., Broadbent, D. M., Harding, S. P., & Zheng, Y. (2016). Convolutional Neural Networks for Diabetic Retinopathy. Procedia Computer Science, 90,200–205https://
doi.org/10.1016/j.procs.2016.07.014

[3] Kermany, D. S., Goldbaum, M., Cai, W., et al. (2018). Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell, 172(5), 1122–1131. https://doi.org/10.1016/j.cell.2018.02.010

[4] Kaggle Diabetic Retinopathy Detection Dataset. (2015).
https://www.kaggle.com/c/diabetic-retinopathy-detection

[5] Simonyan, K., & Zisserman, A. (2015). Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv preprint arXiv:1409.1556. https://arxiv.org/abs/1409.1556

[6] Szegedy, C., Liu, W., Jia, Y., et al. (2015). Going deeper with convolutions. Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR), 1–9.

[7] Abadi, M., Barham, P., Chen, J., et al. (2016). TensorFlow: A system for large-scale machine learning. In 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16), 265–283.

[8] Bradski G. (2000). The OpenCV Library. Dr. Dobb's Journal of Software Tools.