Retinal Image Analysis For Five-Class Eye Disease Detection

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Abstract— Retinal diseases are one of the major causes of vision loss across the world, and early diagnosis plays a vital role in preventing severe complications. Retinal fundus imaging provides a safe and non-invasive way to examine the condition of blood vessels and internal eye structures. In this study, a deep learning-based approach is proposed to classify retinal images into five different disease categories using Convolutional Neural Networks (CNNs) combined with the MobileNet architecture. The system automatically extracts important visual features from retinal images and performs classification with improved efficiency. A dataset containing both normal and diseased retinal images is used for training and evaluation. Several preprocessing techniques such as image resizing, normalization, and augmentation are applied to improve the quality of the dataset. Experimental results show that the proposed model is capable of identifying retinal diseases with good accuracy. This approach can assist medical professionals by providing faster and more reliable screening, especially in large-scale healthcare environments.

Keywords: Retinal images, deep learning, convolutional neural network, MobileNet, medical image classification, eye disease detection, image processing.

I. INTRODUCTION

Eye-related disorders are increasing rapidly due to lifestyle changes, aging, and other health-related issues. Diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration can cause permanent vision loss if they are not detected at an early stage. Traditional diagnosis methods require experienced ophthalmologists and specialized equipment, which may not always be available in rural or underdeveloped areas. Therefore, an automated and cost-effective solution is required to support early diagnosis.Retinal fundus imaging is widely used to observe the internal structure of the eye. The retina contains important information about blood vessels and tissues, which can be analyzed to identify various eye diseases. However, manual examination of retinal images is time-consuming and may lead to errors when large numbers of images are involved.Recent developments in artificial intelligence, especially deep learning, have shown significant improvements in medical image analysis. Convolutional Neural Networks (CNNs) are capable of automatically learning useful features from images without manual feature extraction. In this project, a deep learning model based on the MobileNet architecture is developed to classify retinal images into five different disease categories. The goal of this study is to create a reliable and efficient system that can support medical professionals in the early detection of eye diseases.

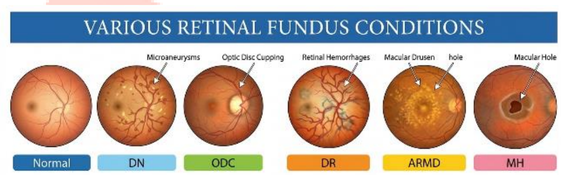

Fig 1.1 Comparison of Various Retinal Conditions

II. OBJECTIVE

The main objective of this project is to design and implement a deep learning model that can accurately classify retinal images into five different eye disease categories. The model is developed using Convolutional Neural Networks along with the MobileNet architecture to improve efficiency and performance.The project also aims to reduce the time required for manual diagnosis and provide a cost-effective method for large-scale screening. By using retinal images as input, the system automatically identifies disease-related patterns and provides classification results. This work focuses on improving accuracy, reducing computational complexity, and developing a system that can be used in real-time healthcare applications.

III. RELATED WORK

Several researchers have explored the use of machine learning and deep learning techniques for medical image analysis. Earlier studies mainly focused on traditional machine learning methods such as Support Vector Machines, Decision Trees, and Logistic Regression. Although these methods produced reasonable results, they required manual feature extraction, which limited their accuracy.With the advancement of deep learning, Convolutional Neural Networks have become widely used for image classification tasks. Many research works have applied CNN-based models to detect eye diseases using retinal fundus images. Pre-trained models such as VGG16, ResNet, and Inception have been successfully used to improve classification accuracy. However, these models require high computational resources and are not always suitable for real-time applications.Recent studies have focused on lightweight architectures such as MobileNet, which provide a good balance between performance and computational efficiency. Researchers have also used data augmentation and image preprocessing techniques to improve the quality of training datasets. These developments show that deep learning can be effectively used for automated retinal disease detection. The current project builds upon these ideas by developing a MobileNet-based CNN model for five-class eye disease classification.

IV. PROPOSED METHODOLOGY

The proposed system aims to improve Retinal disease () prediction through a deep learning model using convolutional neural networks (CNNs) and MobileNet architecture. The MobileNet's lightweight design ensures efficient processing of large retinal image datasets, while CNNs enhance feature extraction capabilities. The system involves preprocessing retinal images through resizing, normalization, and augmentation to optimize data quality. The MobileNet-based CNN model is trained to classify images based on presence or absence. Performance is evaluated using accuracy and other metrics. This approach offers a scalable, cost-effective tool for early detection, supporting timely interventions and improved patient care.

DATA SOURCE:

It used retinal fundus image datasets obtained from publicly available medical sources such as Kaggle and other open repositories. These datasets contain a large number of retinal images collected from different individuals under various clinical conditions. Each subject includes images of the eye that capture the retinal blood vessel structure, which is useful for analyzing cardiovascular health. Since the images are collected from multiple sources using different cameras and imaging conditions, they contain noise and variations, requiring several preprocessing steps such as resizing, normalization, and augmentation to improve quality. Each image is labeled based on the presence or absence of cardiovascular disease or related conditions.

The classification is defined as:
0 = No CVD (Healthy),
1 = DN,
2 = ODC,
3 = DR,
4 = ARMD,
5 = MH.

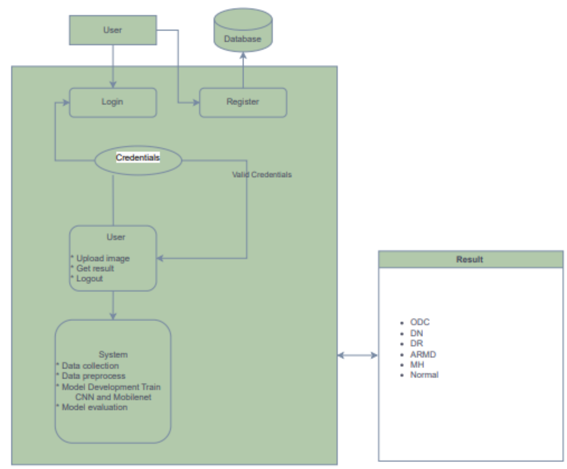

Fig.4.1 Block Diagram

DATA PREPROCESSING:
The retinal fundus images from the dataset were preprocessed to standardize them for model training, as they contained various quality issues such as uneven illumination, low contrast, noise, and variations due to different imaging devices. Preprocessing was performed to improve image clarity, normalize intensity values, and remove unwanted regions. During preprocessing, the following steps were carried out:

- **Image Resizing:** All images were resized to 224 × 224 pixels to match the input size required by the MobileNet model.
- **Normalization:** Pixel values were scaled to a standard range to ensure consistent input and improve model convergence.
- **Data Augmentation:** Techniques such as rotation, flipping, and zooming were applied to increase dataset diversity and reduce overfitting.
- **Cropping:** Images were focused on the retinal region to remove unnecessary background areas and highlight blood vessel_structures.
- **Noise Reduction:** Filtering techniques were used to reduce noise and enhance important retinal features such as blood vessels.

Feature Extraction and Classification: The MobileNet-based Convolutional Neural Network (CNN) was used to automatically extract important features from retinal images, such as blood vessel patterns, thickness, and abnormalities related to cardiovascular conditions. These features were analyzed and used to classify the images based on the presence and severity of cardiovascular disease. The model categorizes the input into different classes such as No CVD, Low Risk, Moderate Risk, High Risk, and Severe Condition based on learned patterns.

AlgorithmImplementation:

The processed images were fed into the MobileNet-based CNN model for training and prediction. The network learns features through convolutional layers and passes them to fully connected layers for classification. Softmax activation was applied in the output layer to generate probability scores for each class. The class with the highest probability was selected as the final prediction. This preprocessing and classification pipeline ensures that the input images are clear, consistent, and suitable for deep learning, improving the model's ability to accurately predict cardiovascular diseases from retinal images.

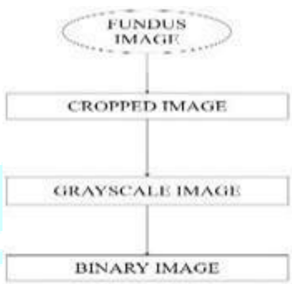

Fig.4.2 Pre-Processing Stage (PPS)

TESTING:

We tested each module in our project to ensure that it performed the required functionality and worked as expected. The main aim of testing was to identify and correct errors before final deployment. Different testing methods such as unit testing, integration testing, functional testing, and system testing were used. Unit testing ensured that individual modules like user login, image upload, and prediction worked correctly. Integration testing verified that all modules functioned together without issues. Functional testing checked whether each feature met the specified requirements. System testing evaluated the overall performance of the project. Black box testing was used to test user interactions, while white box testing focused on internal logic. The testing process mainly concentrated on data input validation, image processing, navigation, and response time. All test cases were executed successfully, and no major errors were found. Overall, the testing confirmed that the system works accurately, meets user requirements, and provides a reliable user experience.

INPUTS	POSITIVE TESTCASE	NEGATIVE TESTCASE
FUNDUS IMAGES	SHOWS THE RANGE OF CVD DISEASE	NORMAL
OTHER IMAGES	GIVEN IMAGE IS NOT RELATED TO THE PROJECT	GIVEN IMAGE IS NOT RELATED TO THE PROJECT

V. RESULT

The proposed model was trained using a retinal fundus image dataset collected from publicly available sources. Preprocessing played an important role as the raw images contained noise due to variations in lighting, camera quality, and focus. During preprocessing, images were resized to 224 × 224 pixels, normalized, and unnecessary background regions were removed to focus on the retinal area. Data augmentation techniques such as rotation, flipping, and zooming were applied to improve dataset diversity and handle class imbalance. The MobileNet-based CNN model was then trained using the processed images. After training, the model achieved good accuracy and showed effective performance during validation. The results indicate that the proposed system can successfully analyze retinal images and predict cardiovascular disease risk with reasonable accuracy. This model can be used as a supportive tool for early detection, helping healthcare professionals in decision-making and improving patient care.black borders and corners were eliminated during preprocessing, and all images were uniformly scaled

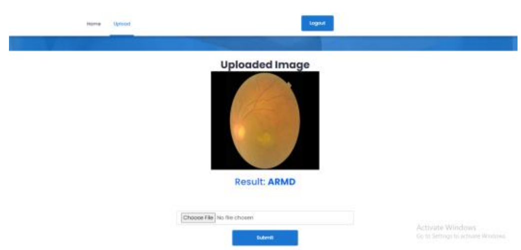

Fig. 5.1 Web Output

Figure 5.1. The picture displays a retinal fundus image.

Classes	Precision	Recall	F1-Score
0	0.99	0.98	0.98
1	0.78	0.95	0.86
2	0.97	0.92	0.94
3	0.92	0.98	0.95
4	0.99	0.98	0.98

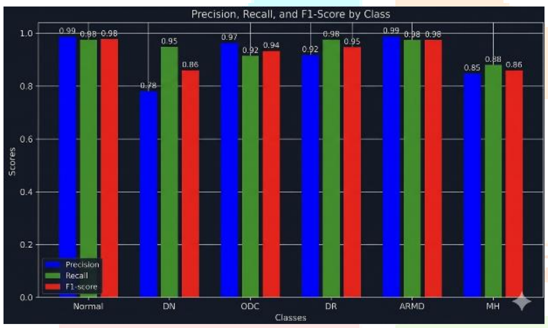

Fig. 5.2 Accuracy Chart

VI. CONCLUSION

Using the MobileNet-based Convolutional Neural Network (CNN) model, the proposed approach effectively predicts cardiovascular diseases from retinal fundus images. By applying efficient preprocessing and data augmentation techniques, the model achieved good accuracy, demonstrating its reliability and performance. This system provides a fast, non-invasive, and cost-effective method for early detection of cardiovascular diseases. The results show that deep learning can play an important role in automating medical image analysis, supporting healthcare professionals in clinical decision-making, and improving overall patient outcomes.

VII. FUTURE SCOPE

To improve the accuracy and generalization of the proposed system, it can be trained on larger and more diverse retinal image datasets. The inclusion of additional clinical data such as patient medical history, blood pressure, and cholesterol levels can further enhance prediction performance. The system can also be extended into a real-time web or mobile application for easy access, especially in remote and rural areas. Future work may focus on combining the MobileNet model with other advanced deep learning architectures to improve detection accuracy and robustness.

APPENDIX

Additional experimental details and performance results are provided to support the main outcomes of this study. The appendix includes confusion matrices for different CVD risk categories, along with accuracy and loss graphs obtained during model training. All supplementary datasets, preprocessing codes, and trained model files used in this project can be made available upon request for academic purposes.

ACKNOWLEDGMENT

The authors express their sincere thanks to the Department of Computer Science and Engineering for providing the necessary facilities and technical support for this project. The authors also acknowledge the valuable guidance and support of the project guide, whose suggestions and encouragement contributed significantly to the successful completion of this work.

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