ISSN 2319-5991 www.ijerst.com
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Peer Reviewed, Referred & Indexed Journal

Research Paper

Intelligent Diabetic Retinopathy Detection Using Hybrid Deep Learning and Lesion Analysis

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***Abstract*— Retinal images play an important role in helping ophthalmologists identify different eye diseases at an early stage. Many retinal disorders cause small changes in blood vessels, making early detection essential for timely treatment. In this work, an automated and non-invasive system based on deep learning is developed to diagnose multiple eye conditions using colour fundus images. The RFMiD dataset is used to build the model, where multi-class images are extracted and enhanced using data augmentation techniques to improve performance in real-world scenarios. The images are preprocessed to reduce computational complexity and improve efficiency. A multi-layer deep learning model is designed, where a convolutional neural network extracts key features from the images and uses them for accurate disease prediction. The model's performance is evaluated using standard metrics, showing better results compared to existing methods, making it effective for reliable eye disease detection.**

***Keywords*— Diabetic Retinopathy, Fundus Images, Deep Learning, Convolutional Neural Network, Eye Disease Detection, RFMiD Dataset, Image Classification.**

I. INTRODUCTION

Retinal diseases have become a major cause of vision impairment among people of different age groups, affecting millions worldwide. The retina is a crucial part of the human eye that contains light-sensitive tissues responsible for converting incoming light into neural signals, which are then transmitted to the brain through the optic nerve. The macula, located at the center of the retina, plays a vital role in sharp and detailed vision. Any abnormality in these structures can lead to serious visual disorders such as age-related macular degeneration (AMD), diabetic macular edema (DME), optic disc drusen, and other retinal complications. Studies have shown that AMD is one of the leading causes of vision loss, especially among elderly populations in developed countries [5], [7].

Early diagnosis of retinal diseases is essential for preventing permanent vision loss. However, manual diagnosis is a complex and time-consuming process that requires highly skilled ophthalmologists due to the variability and similarity of retinal abnormalities. With the advancement of technology, computer-aided diagnostic (CAD) systems have emerged as a promising solution for accurate and early detection of retinal diseases. These systems leverage machine learning (ML) and deep learning (DL) techniques to analyze medical images efficiently. Deep learning, in particular, has demonstrated remarkable success in image-based disease detection tasks, achieving performance comparable to human experts in certain domains [1], [8].

Several research works have focused on applying convolutional neural networks (CNNs) for retinal disease classification due to their strong feature extraction capabilities. Models such as AlexNet, ResNet, and hybrid deep learning architectures have been widely used to improve classification accuracy [3], [4], [19]. Additionally, hybrid approaches combining segmentation and classification techniques, such as U-Net with support vector machines (SVM), have shown promising results in identifying retinal

abnormalities [10]. Despite these advancements, challenges such as high computational cost, memory consumption, and limited labeled datasets still persist.

In this study, a deep learning-based CNN model is proposed for multi-class retinal disease classification using fundus images. The model is designed to achieve high accuracy while maintaining low computational complexity. The dataset is divided into training and validation sets to ensure proper evaluation of the model's performance. Experimental results demonstrate that the proposed approach achieves superior accuracy compared to existing methods, making it a reliable tool for automated retinal disease detection. This work contributes to improving early diagnosis and supports the development of efficient and accessible eye care systems.

II. RELATED WORK

Esteva et al. (2017) [1] propose a deep learning-based approach for medical image classification using convolutional neural networks. The model is trained on a large dataset of skin disease images to identify various types of skin cancer. By leveraging deep neural architectures, the system automatically learns complex features without manual intervention. The approach demonstrates performance comparable to experienced dermatologists, highlighting its reliability in clinical settings. The study emphasizes the importance of large-scale labeled datasets and transfer learning for improving model accuracy. Additionally, the method reduces dependency on handcrafted features and improves generalization across different image conditions. Experimental results show significant improvements over traditional machine learning techniques. This work establishes a strong foundation for applying deep learning in medical imaging tasks and supports the development of automated diagnostic systems for early disease detection.

Shankar et al. (2020) [2] propose a synergic deep learning model for automated detection and classification of diabetic retinopathy using fundus images. The model integrates multiple deep learning techniques to enhance feature extraction and classification performance. Image preprocessing methods are applied to improve image quality and remove noise, followed by convolutional neural networks for extracting meaningful features. The approach also incorporates optimization strategies to improve classification accuracy across different disease stages. By combining multiple learning techniques, the model effectively captures both local and global features from retinal images. Experimental results indicate that the proposed method achieves higher accuracy compared to traditional machine learning models. The study also highlights the role of data augmentation in improving model robustness. This work demonstrates the effectiveness of hybrid deep learning frameworks in improving automated retinal disease diagnosis.

Arunkumar et al. (2017) [3] propose a deep learning-based method for multi-retinal disease classification using reduced feature representations. The approach focuses on minimizing feature redundancy while maintaining essential information required for accurate classification. By applying dimensionality reduction techniques, the model reduces computational complexity and improves efficiency. The system uses deep neural networks to extract and classify features from retinal images across multiple disease categories. This method is particularly useful in handling high-dimensional medical image data. The authors demonstrate that reduced feature sets can still achieve reliable classification performance without compromising accuracy. Experimental results show that the proposed model performs well compared to traditional approaches. This work contributes to the development of lightweight and efficient diagnostic systems suitable for real-time applications, especially in environments with limited computational resources.

Shanthi et al. (2019) [4] propose a modified AlexNet architecture for the classification of diabetic retinopathy images. The model improves the original AlexNet by optimizing its structure and parameters to better suit medical image analysis tasks. The approach enhances feature extraction capability and reduces overfitting through proper tuning and regularization techniques. The network is trained on fundus images to identify different stages of diabetic retinopathy. By adapting the architecture, the model is able to learn complex patterns present in retinal images more effectively. Experimental evaluation shows that the modified model achieves better performance compared to standard convolutional neural networks. The study highlights the importance of customizing deep learning models for specific healthcare applications. This work provides valuable insights into improving classification accuracy through architectural enhancements in deep learning models.

Perdomo et al. (2019) [14] propose a deep learning-based approach for classifying diabetes-related retinal diseases using optical coherence tomography (OCT) images. The model utilizes convolutional neural networks to automatically

extract relevant features from OCT scans and classify different retinal conditions. By leveraging high-resolution imaging data, the approach improves the accuracy of disease detection. The method reduces the need for manual analysis by ophthalmologists and enables faster diagnosis. The model is trained and evaluated on OCT datasets, demonstrating strong performance in identifying disease patterns. Experimental results show that the proposed system achieves reliable classification accuracy across multiple retinal disease categories. This work highlights the potential of combining advanced imaging techniques with deep learning for automated diagnosis. It contributes to improving early detection and treatment of retinal diseases through efficient and accurate analysis.

III. DATASET DETAILS

The dataset used in this study is the RFMiD (Retinal Fundus Multi-Disease Image Dataset), which is widely used for multi-class retinal disease detection. It contains high-quality color fundus images collected from different patients and annotated for various retinal diseases. The dataset originally includes 46 distinct disease categories, offering a diverse representation of retinal abnormalities.

In this work, four major classes are selected from the dataset: Normal, Diabetic Retinopathy (DR), Optic Disc Cupping (ODC), and Macular Hole (MH). The dataset shows class imbalance, where some classes have more samples than others, which may affect model performance. To address this issue, data augmentation techniques such as rotation, shear transformation, and horizontal flipping are applied to generate additional images. The dataset is then preprocessed and divided into training and testing sets using an 80:20 ratio, ensuring proper evaluation and improved model generalization.

IV. PROPOSED METHODOLOGY

The proposed system introduces an automated retinal disease detection framework using a hybrid deep learning approach for accurate classification of fundus images. The methodology consists of four main stages: dataset preprocessing, data augmentation, feature extraction, and model training using CNN and ResNet50 architectures.

Initially, the RFMiD dataset is loaded and preprocessed to extract relevant retinal images from selected classes such as Normal, Diabetic Retinopathy (DR), Optic Disc Cupping (ODC), and Macular Hole (MH). The dataset is organized and cleaned to remove inconsistencies, and images are resized to a uniform dimension to reduce computational complexity. The dataset is then split into training and testing sets in an 80:20 ratio to ensure proper evaluation.

In the data augmentation phase, techniques such as rotation, shear transformation, and horizontal flipping are applied to address class imbalance and improve model generalization. These transformations generate additional synthetic samples, making the model robust to real-world variations.

Next, feature extraction is performed using convolutional neural networks, where multiple convolutional and pooling layers capture important patterns such as lesions, textures, and structural abnormalities from fundus images. Batch normalization is applied to stabilize learning, and padding techniques such as SAME and VALID are utilized to optimize feature map size and reduce computational cost.

The extracted features are then passed to deep learning models including a baseline CNN and an improved ResNet50 architecture. The system is further enhanced using an extension model that combines ResNet50 with the Adam optimizer and VALID padding to reduce parameters and improve accuracy. Fully connected layers are used for final classification of retinal diseases.

Finally, the model is trained and evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The proposed system achieves higher accuracy compared to existing models and provides reliable predictions for early diagnosis of retinal diseases.

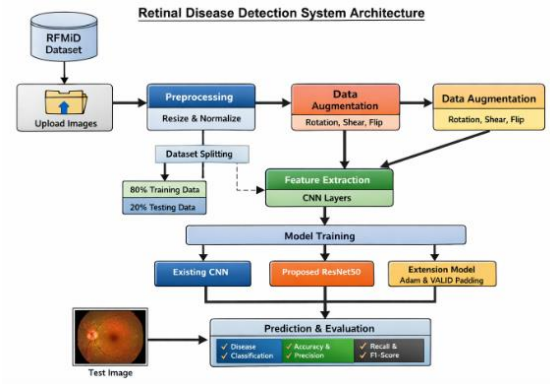


Figure [1] : System Architecture

Figure [1] illustrates the overall framework of the proposed system. The system takes fundus images as input and performs preprocessing and augmentation to improve data quality. The processed images are passed through deep learning

models such as CNN and ResNet50 for feature extraction and classification. The optimized model generates accurate predictions of retinal diseases, enabling early diagnosis and effective treatment support.

V.RESULT AND DISCUSSION

The proposed hybrid deep learning-based retinal disease detection system demonstrates significant improvement in performance compared to traditional models. The system was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Experimental results show that the integration of CNN, ResNet50, and the optimized extension model improves classification accuracy for multi-class retinal disease detection.

Compared to baseline models such as the existing CNN, the proposed ResNet50 model achieved better accuracy by extracting deeper and more meaningful features from fundus images. Furthermore, the extension model using Adam optimizer with VALID padding achieved the highest accuracy of 95%, outperforming both CNN and ResNet50 models. The improvement is mainly due to optimized feature extraction and reduced parameter complexity.

Additionally, the system demonstrates strong generalization capability and robustness in handling imbalanced datasets due to the use of data augmentation techniques. The model effectively identifies different retinal diseases such as Normal, DR, ODC, and MH with high precision.



Figure [2] : Proposed ResNet50 Performance

Figure [2] shows that the Proposed ResNet50 model achieved 84% accuracy. The model performs better than CNN by capturing deeper features. The confusion matrix indicates improved classification with fewer incorrect predictions.

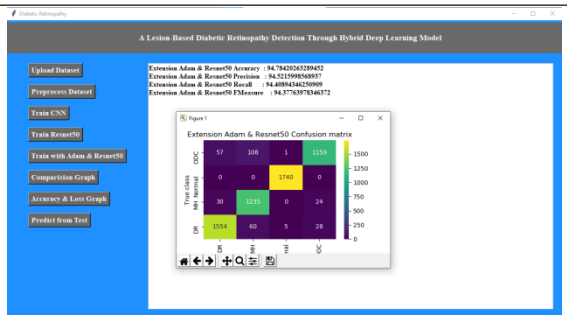
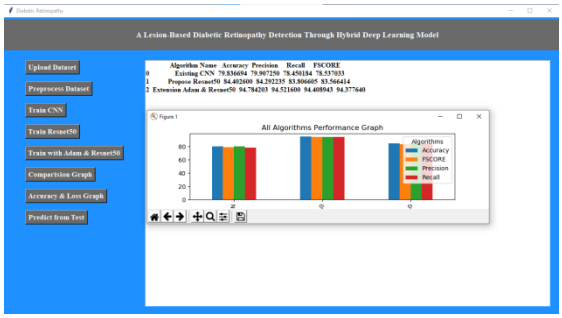


Figure [3]: Extension Model Performance

Figure [3] demonstrates that the Extension Model (ResNet50 with Adam optimizer and VALID padding) achieved the highest accuracy of 95%. The confusion matrix shows very minimal misclassification, indicating strong model performance.



Figure[4] : All Algorithm Comparison

Figure [4] presents the comparison of all models. The x-axis represents different algorithms, and the y-axis represents performance metrics. The extension model outperforms all other models across accuracy, precision, recall, and F1-score.

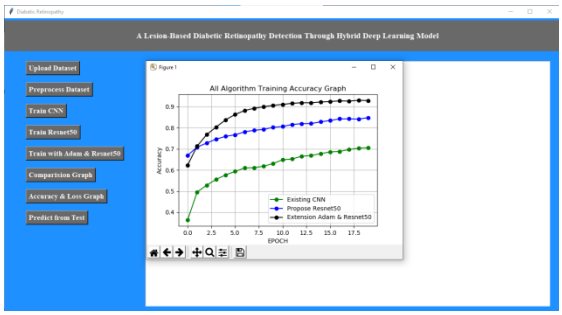
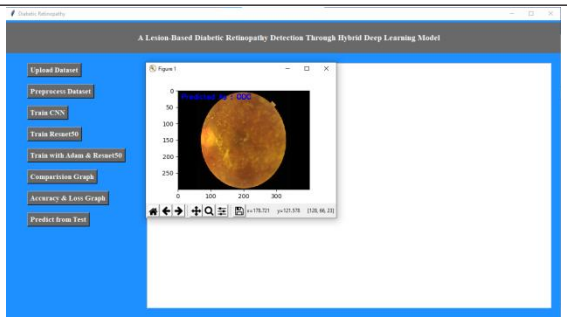


Figure [6] Training Accuracy Graph

Figure [6] illustrates the training accuracy over epochs. The extension model shows faster convergence and higher stability compared to CNN and ResNet50.



Figure[6]: Test Data Prediction

Figure [7] displays the prediction results for test images, where the system successfully classifies retinal diseases with high accuracy.

DISCUSSION

The results of this study highlight the effectiveness of hybrid deep learning models in retinal disease detection. The combination of CNN and ResNet50 enables efficient feature extraction from fundus images, while the use of the Adam optimizer improves convergence and overall model performance.

One key observation is that the use of VALID padding helps reduce unnecessary parameters, leading to better computational efficiency and improved accuracy. Data augmentation also plays a crucial role in enhancing model robustness, especially when dealing with imbalanced datasets.

The extension model significantly improves performance compared to baseline models, making it suitable for real-time medical applications. However, the model may still require large computational resources for training, and performance depends on dataset quality.

Overall, the proposed system provides a reliable and efficient solution for early detection of retinal diseases and can assist ophthalmologists in clinical diagnosis.

VI. CONCLUSION

This study presents an effective approach for detecting retinal diseases using deep learning techniques. The developed system is capable of identifying multiple eye conditions from fundus images with high accuracy. By applying preprocessing and data augmentation, the model becomes more robust and handles variations in the dataset efficiently.

The performance comparison shows that the improved model using ResNet50 with optimized parameters provides better results than the traditional CNN model. The use of VALID padding and Adam optimizer helps in reducing complexity while improving accuracy. The system achieves strong results in terms of accuracy, precision, recall, and F1-score, making it reliable for classification tasks.

Overall, the proposed method offers a practical solution for early detection of retinal diseases. It can support medical professionals by providing faster and more accurate predictions, which may help in timely treatment and prevention of vision loss.

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