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A Hybrid Retinal Diseases Classification Model Using Convolutional Neural Networks and Fundus Images

Anazia Eluemunor Kizito[1]
Department of Information Systems and Technology, Southern Delta University, Ozoro, Delta State

Ubrurhe Ogheneochuko[2]
Department of Information Systems and Technology, Southern Delta University, Ozoro, Delta State

Ogbimi E. Francis[3]
Department of Information Systems and Technology, Southern Delta University, Ozoro, Delta State

Orugba Kenneth Obokparo[4]
Department of Information Systems Southern Delta University, Ozoro, Delta State

Abstract:
Vision problems, particularly retinal diseases, have become increasingly prevalent in recent times. Conditions such as diabetic retinopathy, glaucoma, and cataract are among the leading causes of vision loss worldwide. The burden is especially severe in developing and low-income countries, where access to specialized eye care remains limited. Early detection and accurate classification are vital to prevent irreversible damage and improve patient outcomes. This study introduces a hybrid retinal diseases classification model using convolutional neural networks and fundus images that combines Convolutional Neural Networks with advanced image preprocessing and augmentation techniques to analyze retinal fundus images. The model was trained and validated on both publicly available datasets and real clinical data, ensuring reliability and adaptability across diverse settings. Preprocessing steps such as normalization, noise reduction, and image enhancement improved image quality, while augmentation techniques helped address class imbalance. Experimental results showed strong diagnostic performance, with the model achieving 92.75% accuracy, 88.89% recall, 92.02% specificity, 88.89% precision, and a 90.57% F1-score. These results highlight the system's ability to minimize errors and deliver consistent outcomes. The model provides a scalable, efficient, and clinically relevant tool to support ophthalmologists in early disease detection, particularly in underserved communities, offering a promising step toward reducing preventable blindness.

Keywords: Retinal Disease Classification, Convolutional Neural Networks, Fundus Images, Diabetic Retinopathy, Glaucoma and Cataract

1. Introduction

Notable retinal diseases such as glaucoma, diabetic retinopathy, and age-related macular degeneration remain among the leading causes of vision loss worldwide. Millions of people are affected each year, yet many cases of blindness could be prevented through timely diagnosis and treatment [1]. Conventional screening relies heavily on ophthalmologists who analyze fundus images (photographs) from the back of the eye that capture the retina, blood vessels, and optic disc. While effective, this approach is often time-consuming, subjective, and difficult to scale, particularly in rural or resource-limited settings where trained specialists are scarce [2].

The rise of artificial intelligence, especially convolutional neural networks, has transformed the way medical images are interpreted [3]. Convolutional neural networks excel at detecting subtle patterns in fundus images that may go unnoticed by the human eye, enabling automated diagnosis of retinal diseases with impressive accuracy [4]. These systems have great potential to support large-scale screening programs, reduce the workload of healthcare professionals, and expand access to quality eye care. However, as noted by [5], single convolutional neural network models face important challenges. Retinal datasets are often imbalanced, with some conditions occurring more frequently than others, which can make predictions to be bias [6]. In addition, differences in image quality caused by lighting, focus, or device variations as well as patient-specific factors such as pigmentation and retinal anatomy introduce inconsistencies that limit performance. Consequently, convolutional neural network-based systems may struggle to maintain accuracy outside controlled research environments [7].

To address these challenges, researchers are increasingly adopting hybrid approaches that combine multiple convolutional neural network architectures with advanced preprocessing techniques [8]. These hybrid models are capable of detecting both fine-grained features, such as microaneurysms and small lesions, and larger anatomical patterns, including vascular networks and optic disc changes. By integrating the complementary strengths of different convolutional neural networks and standardizing image inputs, hybrid models demonstrate improved accuracy, sensitivity, and robustness, making them more adaptable to real-world clinical conditions [9].

This hybrid retinal disease classification model leverages convolutional neural networks and fundus imaging to deliver more precise and reliable diagnoses. It is designed to minimize misclassification, handle class imbalances effectively, and adapt to diverse healthcare environments, including mobile and community-based programs [10]. Beyond its technical advantages, this work aims to improve early detection, reduce preventable blindness, and provide healthcare professionals with scalable, consistent diagnostic support [11]. By bridging advanced technology with urgent clinical needs, the hybrid model has the potential to transform eye care delivery system especially in regions where timely access to specialists remains limited.

2. Review of Related Literature

Glaucoma, diabetic retinopathy, and age-related macular degeneration are major retinal diseases that can cause irreversible blindness. Their prevalence continues to rise, largely due to the global increase in diabetes and aging populations. Early detection is therefore critical, as timely intervention can preserve vision and reduce the risk of progression to blindness [12]. However, conventional diagnostic methods that depend on expert interpretation of retinal fundus images are resource-intensive and prone to inter-observer variability, highlighting the need for automated and reliable diagnostic solutions.

Earlier research primarily emphasized hand-crafted feature extraction, focusing on vessel morphology, texture descriptors, and lesion-specific characteristics, which were analyzed using machine learning algorithms such as support vector machines and random forests [13]. Although these approaches laid the foundation for computer-aided retinal diagnosis, they were limited in their ability to capture the subtle and complex manifestations of retinal diseases [14]. The emergence of deep learning, particularly convolutional neural networks, has since transformed retinal image analysis. convolutional neural networks-based models can learn discriminative features directly from fundus images and have demonstrated remarkable diagnostic performance across multiple retinal conditions [15]. Furthermore, transfer learning leveraging pre-trained weights from large-scale datasets like ImageNet has proven highly valuable in addressing the scarcity of annotated medical images [16].

Despite these advances, real-world challenges persist. Variability in fundus image quality, caused by illumination differences, resolution inconsistencies, and patient-specific anatomical variations, often complicates analysis [17]. To address these issues, preprocessing techniques such as contrast-limited adaptive histogram equalization and image normalization are widely applied to enhance clarity [18]. In addition, segmentation methods play a crucial role in isolating key retinal structures, including blood vessels, the optic disc, and the macula. U-Net and its derivatives have become the benchmark architectures for retinal segmentation, improving both classification outcomes and interpretability [19]. Complementary techniques such as gradient-weighted class activation mapping further strengthen trust in automated systems

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by highlighting the regions of an image that drive model predictions [20].

Nonetheless, convolutional neural networks-based systems still face obstacles such as class imbalance, limited generalization across datasets, and difficulty detecting lesions of varying scales [21]. To overcome these limitations, hybrid approaches have been explored. In some models, Convolutional neural networks are employed as feature extractors, with their outputs refined by classical classifiers like support vector machines or random forests. Other frameworks adopt multi-branch architectures that integrate local lesion-level features with global contextual information, thereby improving robustness to variability in lesion size and presentation.

More recently, convolutional neural networks–transformer hybrids have emerged as promising solutions. While convolutional neural networks excel at capturing localized patterns, Transformers are particularly effective for modeling long-range dependencies in images, and their combination has shown improved accuracy and generalization [22]. Ensemble strategies have also proven effective, with techniques such as majority voting, weighted averaging, and stacking reducing variance and enhancing stability across diverse datasets.

Fundus imaging remains one of the most widely adopted tools for diagnosing and monitoring retinal diseases [23]. This non-invasive technique captures a detailed two-dimensional view of the posterior segment of the eye, revealing key anatomical landmarks such as the optic disc, macula, fovea, and vascular networks. Pathological signs such as microaneurysms, hemorrhages, exudates, or optic nerve damage serve as early indicators of disease [24]. While advanced modalities like optical coherence tomography offer high-resolution, cross-sectional views of retinal layers, fundus photography remains more accessible, affordable, and suitable for large-scale screening and follow-up, especially in resource-limited settings [25, 26]. Its ability to provide a wide-field overview has solidified its role as a cornerstone of ophthalmic diagnostics.

Despite its importance, the interpretation of fundus images is labor-intensive and subjective, depending heavily on ophthalmologists and trained graders [27]. To address these challenges, computer-aided diagnostic systems have gained momentum, with deep learning and convolutional neural networks-based approaches leading the way [28]. These systems can automatically identify disease-relevant patterns from fundus photographs, offering scalability, efficiency, and enhanced accuracy for retinal disease screening.

Recent studies further reinforce this potential. For example, [29] proposed a deep learning framework for retinal disease diagnosis that reduced diagnostic errors associated with manual interpretation while improving efficiency for clinicians. Similarly, [30] developed an artificial intelligence model capable of analyzing optical coherence tomography images and classifying them into four retinal disease categories. Their findings demonstrated that automated methods consistently outperformed traditional approaches, particularly in detecting early-stage disease, thereby improving both diagnosis and management of retinal conditions that might otherwise lead to irreversible vision loss.

3. Methodology and System Design

3.1. Method Used

The Convolutional Neural Networks algorithm was chosen because are it is highly effective in handling large datasets and identifying intricate patterns, making them ideal for medical image analysis. They interpret complex visual inputs by learning hierarchical representations of retinal images, which is crucial for accurate disease predictive. The methodology begins with collecting a comprehensive dataset of retinal images from Kaggle data source repository. Kaggle is a widely recognized platform that hosts high-quality datasets suitable for developing, training, and testing machine learning and AI models. Its extensive resources make it a reliable source for data related to disease detection and prediction across various medical conditions.

The process of a hybrid retinal disease classification model using convolutional neural networks and fundus images begins with the collection of retinal image datasets, which serve as the foundation for building and testing the system. These images are cleaned and standardized through preprocessing steps such as resizing, normalization, enhancement, and augmentation to improve quality and diversity. A deep learning architecture, typically a convolutional neural network, is then developed to automatically extract and learn meaningful patterns from the images. The model is trained using these processed images, with its parameters optimized to improve accuracy and minimize errors. Once trained, the system is validated and tested on independent datasets to ensure it performs reliably on unseen cases. It is further evaluated across different clinical scenarios to confirm robustness under varying conditions, after which its performance is compared with traditional prediction methods to highlight improvements in sensitivity, specificity, and overall diagnostic accuracy. Based on the results, refinements are made to fine-tune the model and address any limitations before deployment. In its final stage, the system is integrated into real-world workflows where it is monitored for consistency, and it produces outputs in the form of disease predictions, probability scores, and visual explanations that support clinicians in making confident and informed decisions.

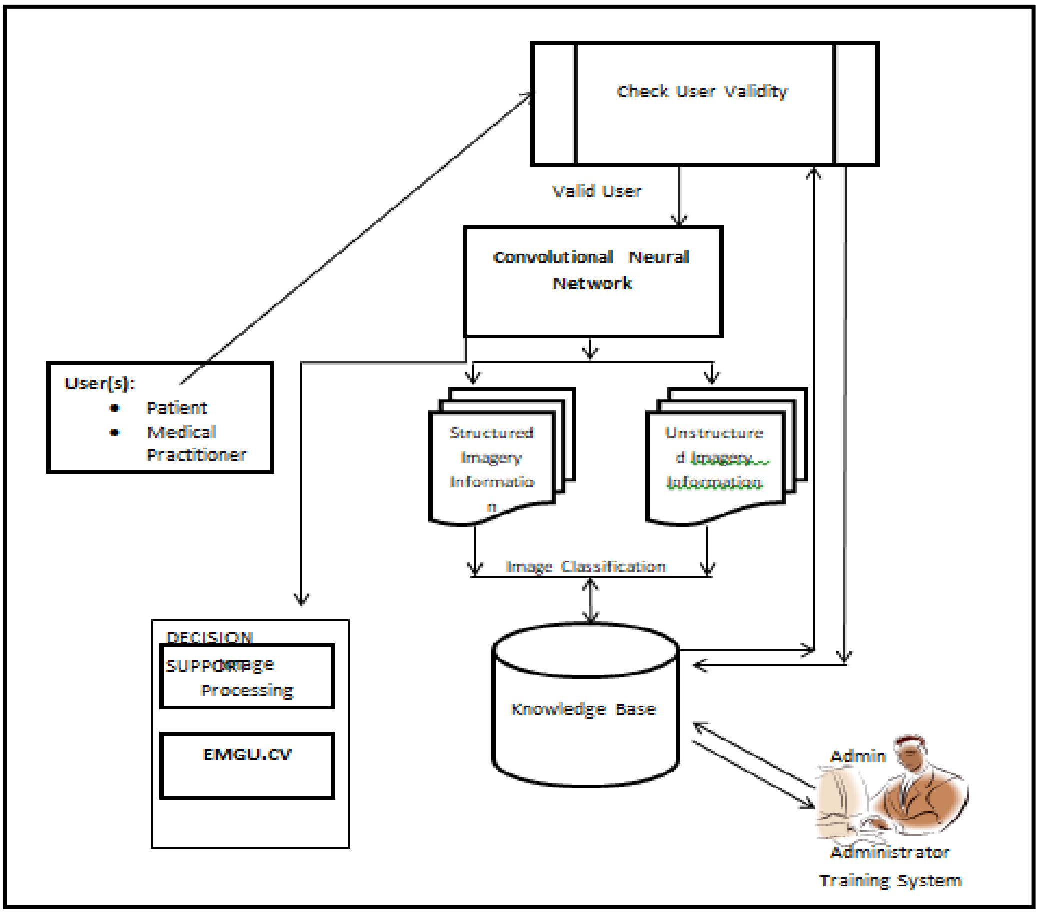

Figure 1: Architecture of mode

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3.2. Components of the system

i. Input Layer

The system begins with the input of raw retinal fundus images. These are preprocessed to ensure consistency by resizing, normalizing pixel intensities, and reducing noise or illumination artifacts. Data augmentation such as rotation, flipping, zooming, and brightness adjustments—further improves generalization. The result is a set of clean, standardized images ready for analysis

ii. Feature Extraction Module

Convolutional neural networks automatically learn visual patterns from the images. Early layers capture simple features like edges and blood vessels, while deeper layers identify disease-specific signs such as microaneurysms, hemorrhages, or optic disc changes. Pre-trained backbones like ResNet, DenseNet, or EfficientNet are often used to boost efficiency and accuracy.

iii. Hybrid Feature Fusion Layer

To enhance representation, convolutional neural networks-derived features are combined with clinically meaningful descriptors such as vessel density or cup-to-disc ratio. Fusion techniques ranging from concatenation to attention mechanisms create a rich feature vector that balances deep learning power with domain-specific knowledge.

iv. Classification Head

The fused features are processed through dense layers that generate predictive outcomes. Dropout, batch normalization, and other regularization techniques help prevent overfitting. A softmax or sigmoid activation function then produces probability scores across disease categories.

v. Decision Module

This module interprets the probability scores and assigns the most likely diagnosis, whether binary (disease vs. normal), multi-class, or severity grading. Clinically defined thresholds can be applied to ensure reliability.

vi. Explainability and Visualization

To build trust, techniques like Grad-CAM and saliency maps highlight image regions driving predictions. These visual cues allow ophthalmologists to confirm that the system focuses on clinically relevant features, improving transparency and adoption.

vii. Training and Optimization Module

Model training involves adjusting parameters with loss functions such as cross-entropy or focal loss, optimized using algorithms like Adam or SGD with momentum. Regularization strategies—weight decay, dropout, label smoothing further improve generalization.

viii. Evaluation Module

Performance is measured using metrics such as accuracy, sensitivity, specificity, F1-score, and AUC. For clinical safety, particular emphasis is placed on minimizing false negatives. Confusion matrices and ROC curves provide additional insights into model behavior.

ix. Deployment Layer

Finally, the trained model is packaged for real-world use, often as an API or mobile/web application. Clinicians can upload fundus images and instantly receive diagnostic predictions with confidence scores, supported by visualization tools like heatmaps. This ensures the system serves not just as a diagnostic engine, but as a practical, explainable assistant in clinical practice.

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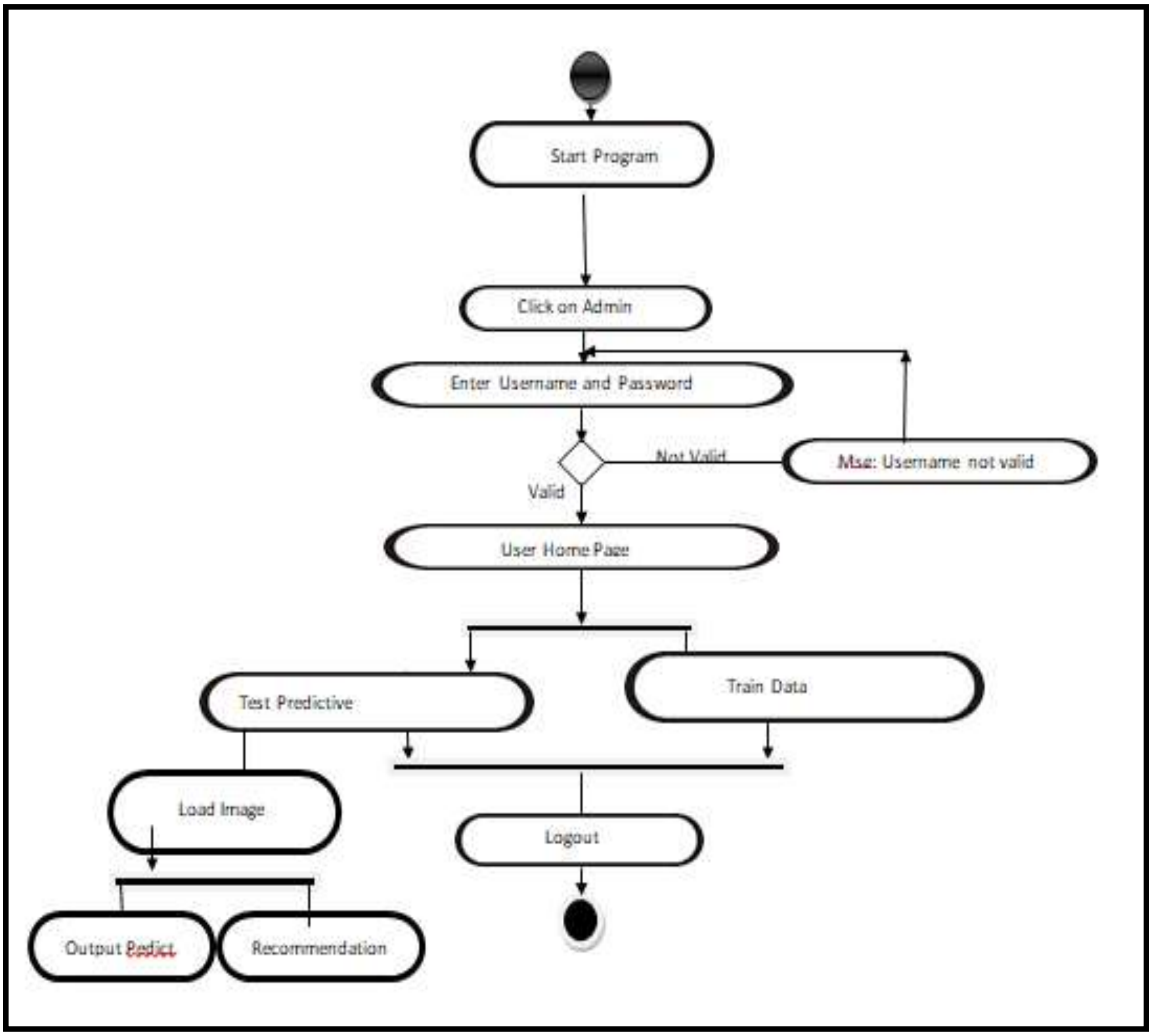

Figure 2: Activity Diagram of the model

3.3. System Implementation

i. Experimentation Setup

This stage centers on model development and data preparation. It starts with collecting retinal image datasets labeled with conditions such as diabetic retinopathy, glaucoma, and cataracts. Supporting metadata is stored in a SQL Server database to ensure efficient organization and easy retrieval. To improve data quality and consistency, preprocessing techniques like normalization, augmentation, and resizing are applied. The convolutional neural networks are built and trained using ML.Net to extract features and classify the images. Different architectures, including ResNet and MobileNet, are tested to determine the best balance between accuracy and computational efficiency. Key hyperparameters such as learning rate, batch size, and number of epochs are carefully tuned to optimize performance. Once a robust model is achieved, it is packaged as a .zip file, ready for deployment in the next stage.

ii. Performance Metrics

The trained model is thoroughly evaluated using key metrics essential in clinical diagnostics, including recall, specificity, and the area under the curve. Sensitivity reflects the model's ability to correctly detect positive cases, while specificity measures its accuracy in identifying negative cases. The area under the curve offers a comprehensive view of the model's overall classification strength.

To ensure reliable performance, cross-validation is applied, with results averaged across folds to assess consistency and robustness. The model's outcomes are also compared against traditional diagnostic methods and state-of-the-art systems, highlighting its advantages in accuracy, efficiency, and scalability.

3.4. Data Presentation

This stage transforms raw retinal image data into a structured format that reveals key patterns and supports system validation. The dataset, which includes images labeled as diabetic retinopathy, cataracts, glaucoma, or normal retina, undergoes preprocessing steps such as normalization, augmentation, and enhancement to ensure consistency and reliability. The processed data are then visualized to show category distributions, the effects of preprocessing, and relevant correlations. These refined datasets are used to train and test the convolutional neural networks-based diagnostic model, with performance evaluated using metrics like accuracy, sensitivity, specificity and area under the curve. To further interpret results and compare them with manual diagnostic methods, visual tools such as confusion matrices, bar charts, and ROC curves are employed.

4. Result and Discussion

4.1. Result Evaluation Performance

The model had great improvement with an overall accuracy of 92.75%, recall value of 88.89% specificity of 92.02%, precision of 88.89% and F1-score of 90.57. These results confirms the model's reliability in distinguishing between diseased and healthy retinal cases, the model demonstrates strong diagnostic performance by minimizing missed detections while accurately identifying normal samples. This balanced outcome further underscores its robustness, effectively managing the trade-off between false positives and false negatives. This gives the model potential as a scalable and dependable diagnostic tool for clinical practice and large-scale screening. While performance is highly encouraging, future work could focus on reducing false positives through dataset expansion and advanced preprocessing. Overall, the system offers a practical pathway toward improving early detection and management of retinal diseases.

Below are some of the output pages of the model;

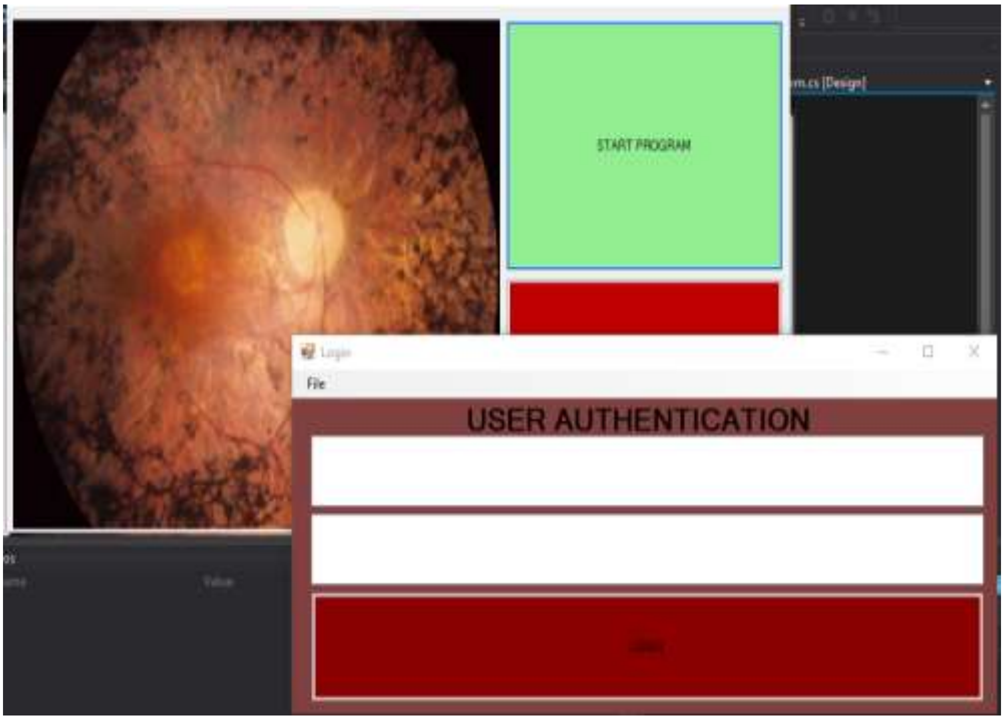

Figure 3: Homepage of the model

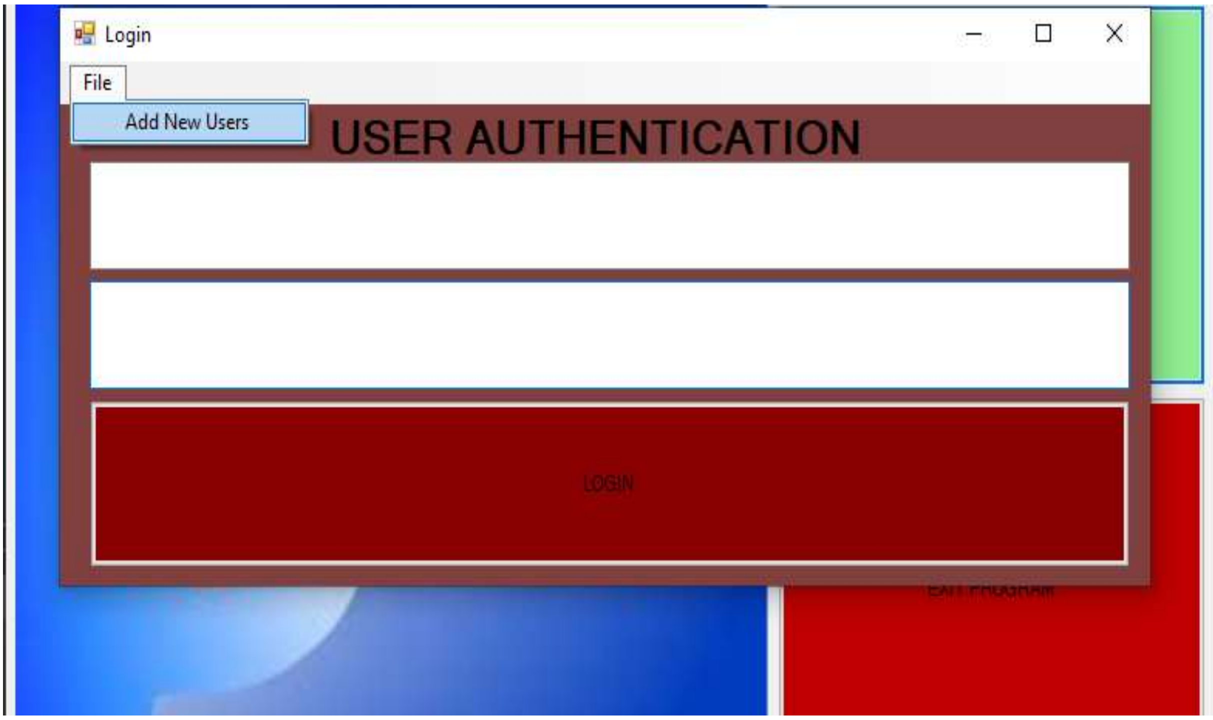

Figure 4: Log-on Module of the model

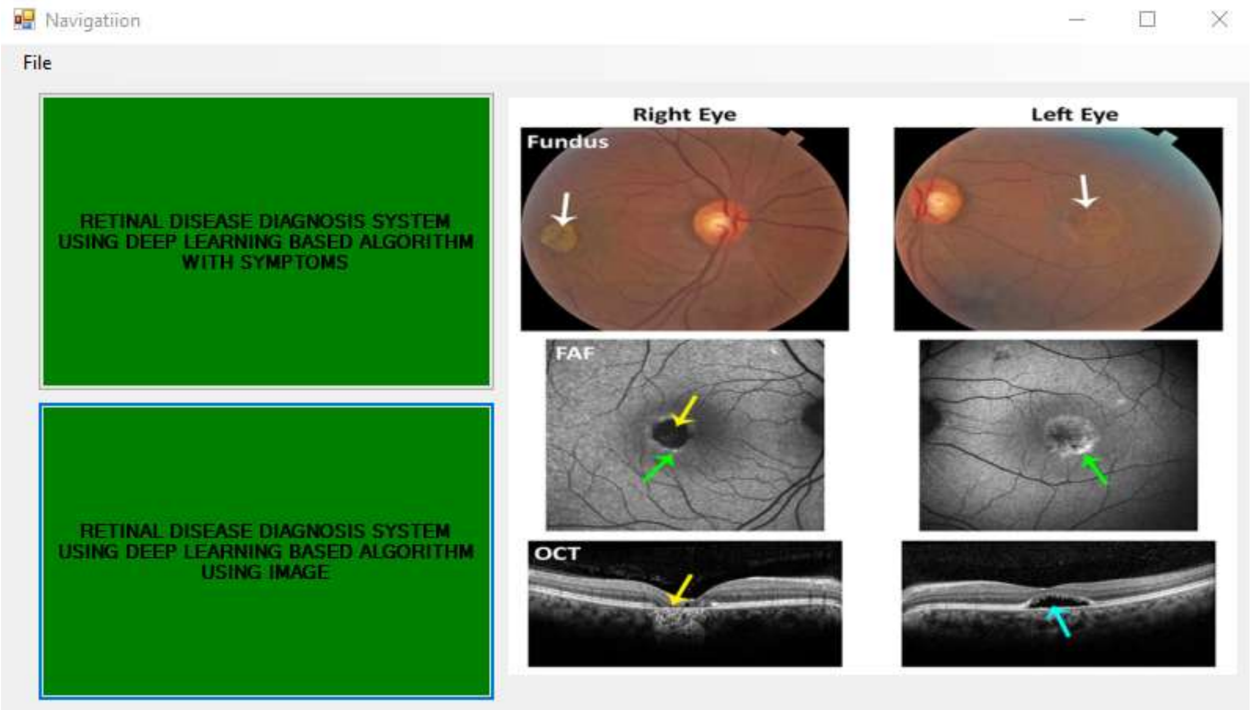

Figure 5: Prediction Main Page of the model

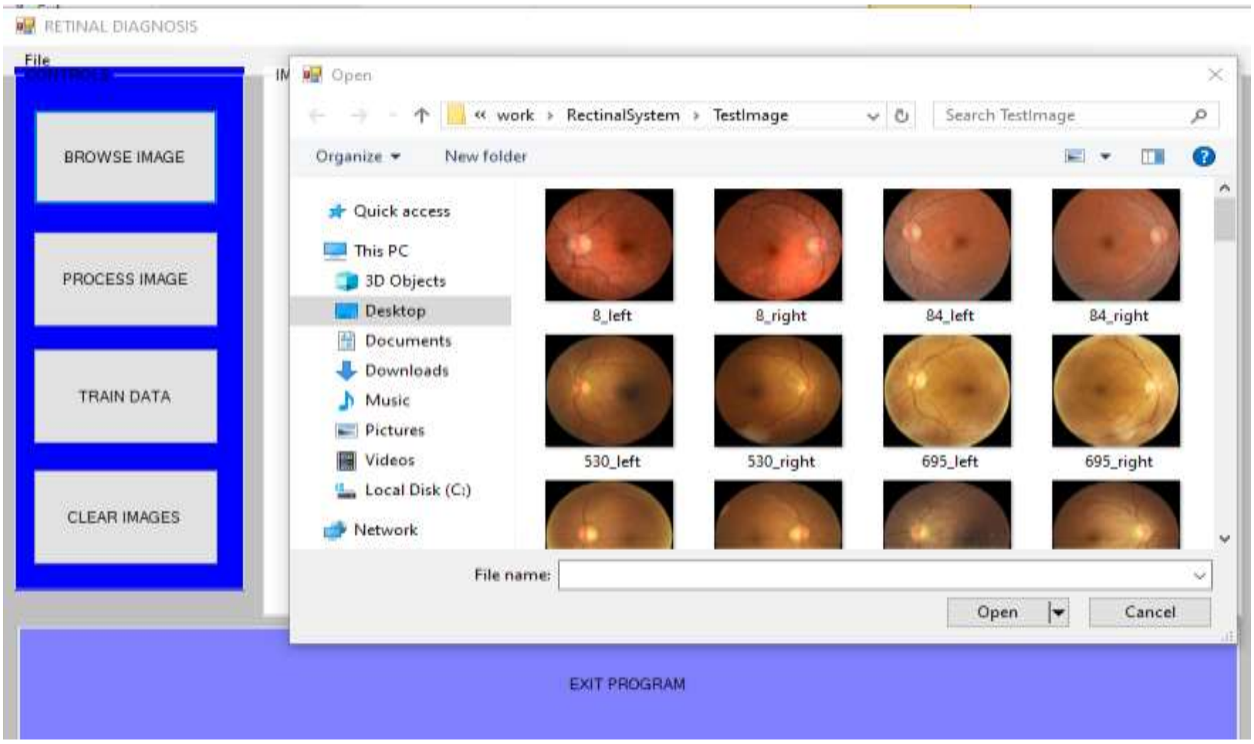

Figure 6: Prediction using retinal images

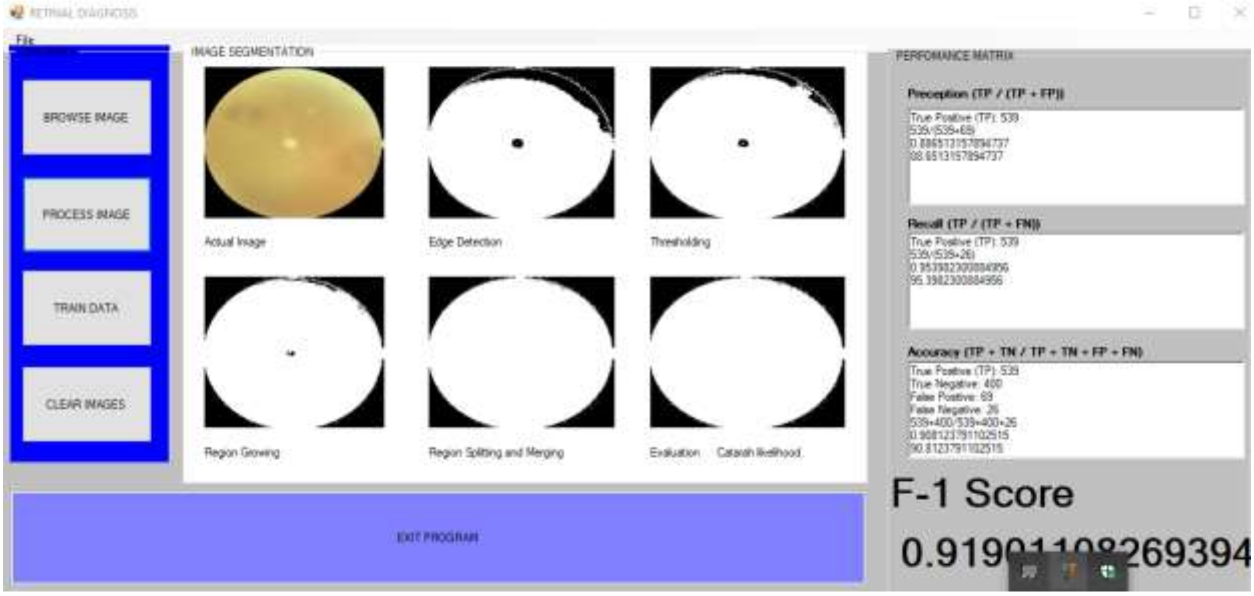

Figure 7: The model's result presentation

Table 2: Actual Test Result versus Expected Test Result

Actual Test Done	Expected Result
Training Module The training module was evaluated using both programmer-generated test data and real-world data obtained from the case study.	The training phase was successful, as the inference engine effectively processed every detail of each ailment or cancerous condition and generated accurate outputs.
User Registration Module: This stage was tested using both programmer-generated data and real patient data obtained from the hospital. These datasets primarily contained basic patient identification information.	The registration module functioned as expected, though some mobile devices initially failed to display the UI/UX correctly. However, by tracing and adjusting the Cascading Style Sheets (CSS) associated with the module, the issue was resolved.
Training Module: The training module was tested using both programmer-developed data and real data obtained from the case study	The training phase was successful, as the inference engine accurately processed every detail of the automobile faults and generated the corresponding outputs
User Registration Module: This stage was tested using both programmer-generated data and real hospital data, consisting of basic information required to verify a valid user.	The registration module functioned as expected; however, some mobile devices did not display the UI/UX correctly. The issue was traced to the Cascading Style Sheets (CSS) in the module, and after adjustments, it was resolved.

Table2: Confusion Matrix

	Predicted Positive (Disease)	Predicted Negative (Healthy)
Actual Positive (Disease)	True Positive (TP): Correctly identified diseased cases.	False Negative (FN): Diseased cases incorrectly classified as healthy
Actual Negative (Healthy)	False Positive (FP): Healthy cases incorrectly classified as diseased	True Negative (TN): Correctly identified healthy cases

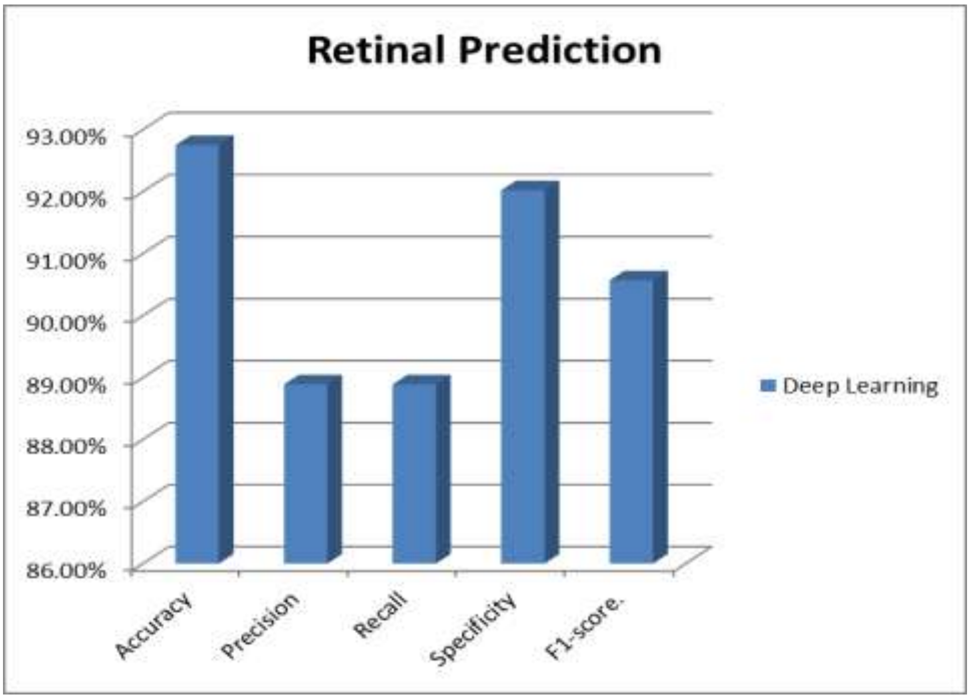

Figure 8: Bar Chart for performance metrics

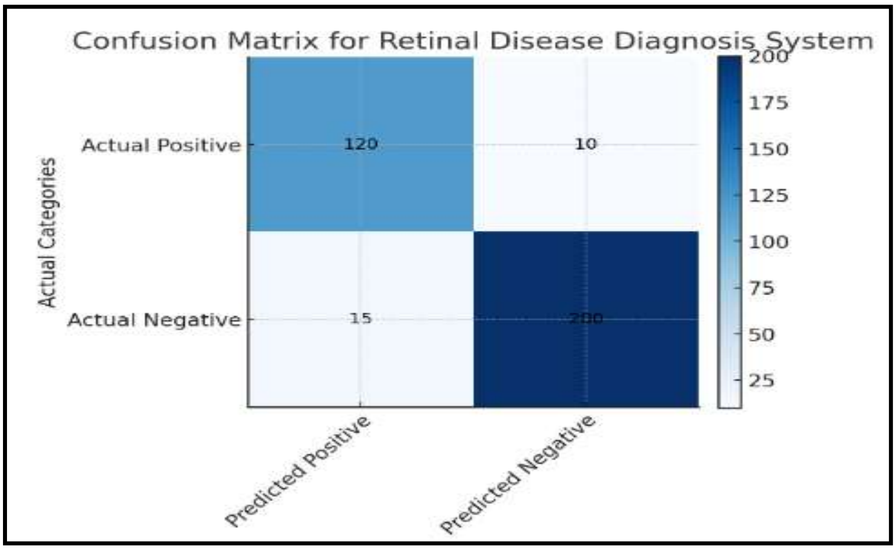

Figure 9: Confusion matrix output

5. Summary

This study presents the development of a retinal disease prediction system leveraging convolutional neural networks and advanced image processing techniques known a hybrid retinal diseases classification model using convolutional neural networks and fundus images The system is designed to enhance early detection and classification of retinal diseases particularly diabetic retinopathy, glaucoma, cataract, and normal cases using retinal fundus images. By combining convolutional neural networks with robust preprocessing methods, the system reduces diagnostic time, minimizes human error, and supports timely medical intervention. The model demonstrated substantial improvement, achieving an overall accuracy of 92.75%, recall of 88.89%, specificity of 92.02%, precision of 88.89%, and an F1-score of 90.57%, thereby confirming its strong predictive performance**.** Real-world testing further demonstrated its efficiency and consistency, particularly in environments with limited access to ophthalmologists.

This model has proven to be a reliable and effective tool for detecting and classifying retinal conditions, with notable success in identifying diabetic retinopathy. Its use of deep learning techniques enables it to surpass traditional manual diagnostic approaches in both speed and accuracy. The high performance metrics recorded during testing validate its clinical relevance and practical applicability. By accurately classifying retinal images and facilitating early intervention, the system offers a scalable solution for healthcare delivery, especially in underserved regions. It holds strong potential for supporting healthcare professionals in improving diagnosis and patient outcomes.

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