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Development of an Enhanced Retinal Disease Predictive System using Convolutional Neural Network

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ABSTRACT

Retinal diseases such as diabetic retinopathy, glaucoma, central serous retinopathy, age-related macular degeneration (AMD), and retinitis remained among the primary causes of visual impairment and blindness worldwide. Early and accurate detection plays a vital role in preventing irreversible vision loss and improving patient outcomes. Despite the significant advancements with the integration of machine learning techniques, automated retinal disease diagnosis still rely heavily on traditional machine learning models such as Support Vector Machines (SVM) for classification tasks, and .predicted one retinal disease. Thus, such SVM models suffer low-dimensional data, and their performance in handling complex high-dimensional retinal images is limited. Therefore, this research presents the development of an enhanced retinal disease predictive system using Convolutional Neural Networks (CNNs) to classify retinal fundus images into four categories three disease types and a normal class. The system was designed and implemented using Python programming language, utilizing libraries such as TensorFlow, Keras, NumPy, Matplotlib, and OpenCV. The development process followed structured phases: Requirement Analysis, System Design, Implementation, Testing, Deployment, and Maintenance. The system also incorporated a mathematical model of CNN layers including convolution, activation (ReLU), pooling, and fully connected layers optimized to learn critical visual patterns from retinal images. A comprehensive preprocessing pipeline was further implemented to enhance image clarity, normalize lighting variations, and standardize input size and format. The model was trained on a dataset of 4,217 images (sourced from Kaggle), split into training, validation, and test sets. The evaluation of this CNN-based model achieved a classification accuracy of 91%, with precision, recall, and F1-scores consistently above 88% across all classes. The system supports both static image uploads and real-time webcam capture, enabling flexible use in clinical or field settings. Evaluation through confusion matrix analysis revealed minimal false predictions, demonstrating high reliability. This study confirms the potential of CNN-based systems in automating retinal disease diagnosis and supporting ophthalmologists with faster, more accurate screening tools.

Keywords: Central serous retinopathy, convolutional neural networks, models, prediction system, retinal disorder

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1.0 Introduction

Retinal diseases are a leading cause of vision impairment and blindness worldwide. Early and accurate predictions are crucial for effective treatment and prevention of vision loss. Traditional methods of retinal prediction rely heavily on the expertise of ophthalmologists who manually examine retinal images a process that is time-consuming and subject to human error. Convolutional neural network algorithms, however, offer a significant advantage by automating the analysis process, thereby reducing the burden on medical professionals and increasing predictive accuracy (Li et al., 2020). The detection of retinal diseases presents a classical machine learning classification challenge. Our work addresses this challenge by enhancing retinal disease detection from scanned optical coherence tomography (OCT) images of the retina across four distinct classes of retinal states, namely CNV, drusen, DME, and normal. With the rising utilization of optical coherence tomography (OCT) in medical science, a computer-assisted predictive system holds great potential for reliably and successfully detecting retinal diseases.Such a system will significantly aid in the treatment and monitoring of these conditions.

The prediction of retinal diseases presents a significant challenge in healthcare, given their prevalence and potential for vision impairment if not promptly identified and treated. Traditionally, predictive relies on manual examination of retinal images by skilled ophthalmologists, which can be time-consuming and subject to human error. However, recent strides in deep learning offer promising prospects for automating and improving this diagnostic process. An inherent strength of deep learning-based systems lies in their capacity to handle diverse and complex datasets, making them well-suited for the nuanced nature of retinal diseases. With the availability of annotated retinal image repositories, researchers have trained deep learning models to detect subtle pathological changes indicative of various conditions, such as diabetic retinopathy, age-related macular degeneration, and glaucoma (Smith et al., 2023).

Recent advancements in retinal disease prediction leverage deep learning algorithms, which have revolutionized medical imaging and diagnostics. Deep learning, a subset of machine learning, involves training neural networks with large amounts of data to recognize patterns and make predictions. Convolutional Neural Networks (CNNs), a type of deep learning model, have been particularly effective in analyzing medical images, including retinal images captured through fundus photography, optical coherence tomography (OCT), and ultra-wide-field fundus imaging (UFI) (Litjens et al., 2017; Ting et al., 2019). A technique that is based on deep learning is developed for categorized patient retinal fundus images into classes according to the severity level of the illness. The advances in science and technology have improved standard of living by making their lives easier, safer, and more convenient to live (Kumar and Tewari,2022).Similar to the human brain, CNN comprises multiple neurons organized in layers (Ting et al., 2018; Zhao et al., 2020). The principal layers of CNN include the convolutional layer, pooling layer, and fully connected layer (Ting et al., 2018). The convolutional layer performs primary filtering (kernel filtering) of input data (Orlando et al., 2018; Ting et al., 2018; Karthik and Mahadevappa, 2023), where the input image undergoes kernel filtering to generate a convolved matrix as output (Chan et al., 2017; Bogunovi et al., 2019; Karthik and Mahadevappa, 2023). Recent studies have underscored the effectiveness of deep learning approaches in retinal disease prediction, often surpassing human experts in accuracy. For instance, Jones et al. (2024) demonstrated the superior performance of a convolutional neural network (CNN) in identifying diabetic retinopathy from fundus photographs, achieving a sensitivity of 95% and specificity of 97%, outperforming experienced ophthalmologists.

Ultra-wide-field fundus imaging (UFI) provides comprehensive visualization of the retina, including peripheral regions that are not visible with standard fundus photography. This advanced imaging technique is particularly useful for diagnosing retinal diseases that affect the peripheral retina, such as retinal tears and detachments. Integrating deep learning models with UFI has shown great promise in enhancing diagnostic accuracy. A recent study by Zhang *et al*. (2021) reported that a deep learning-based system using UFI achieved high performance in detecting and grading various retinal diseases, underscoring the potential of this approach in improving clinical outcomes (Zhang et al., 2021).In diseases such as Central Serous Retinopathy (CSR), early detection is crucial to preventing irreversible vision loss. Nonetheless, reliance on handcrafted feature extraction and limited imaging modalities may introduce biases and reduce the robustness of predictive systems. To address these critical gaps, this study advances beyond conventional methods by employing a CNN-based framework that directly learns discriminative features from raw retinal images without manual intervention. This approach significantly enhances detection accuracy, operational efficiency, and scalability for real-world clinical use. Therefore, this study is to develop an enhanced retinal disease predictive system using convolutional neural network. The results of this research with help in enhancing retinal disease predictive systems, which will be beneficial by providing earlier and more accurate diagnoses.

2.0 Materials and Methods

2.1 Software Methodology Adopted

This research adopts the Waterfall Model as its software development methodology. The Waterfall Model is a linear and sequential approach that is well-suited for structured and well-defined projects such as the development of a deep learning-based predictive system. Each phase in the Waterfall Model must be completed before the next begins, ensuring systematic progress and comprehensive documentation throughout the software lifecycle. Figure 1 shows that the methodology was selected due to its clarity, ease of tracking progress, and suitability for academically and clinically oriented systems.

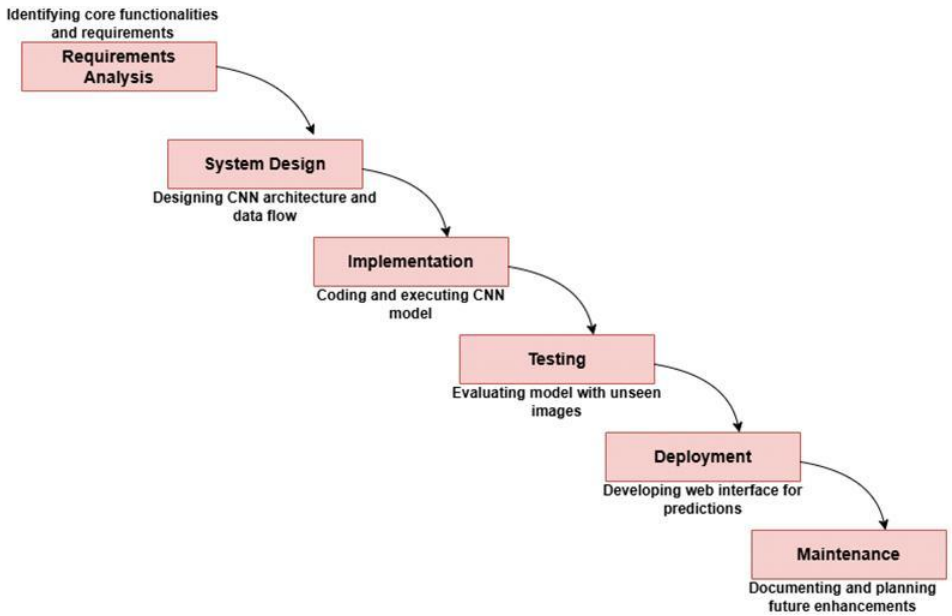


Figure 1: Waterfall Methodology for the developed system

2.2 Data Collection

The dataset utilized in this research was sourced from the Kaggle data repository, a reputable platform that provides diverse and high-quality datasets suitable for training and evaluating machine learning and artificial intelligence models. For this study, a specialized dataset comprising Optical Coherence Tomography (OCT) images related to retinal diseases was employed. The dataset contains a total of 4,217 labeled images categorized into four classes: Normal, Central Serous Retinopathy, Glaucoma, and Diabetic Retinopathy. These images were instrumental in training and testing the Convolutional Neural Network (CNN) model for accurate classification and prediction of retinal conditions. Table 1 showcases the breakdown of the dataset for each class.

Table 1: Breakdown of the dataset

Category	Number of Files
Central Serous Retinopathy	1,038
Diabetic Retinopathy	1,098
Glaucoma	1,007
Normal	1,074
Total	4,217

2.3 Analysis of the Existing System

Central Serous Retinopathy (CSR) is a retinal disorder that impairs vision and, if untreated, can lead to permanent blindness. CSR results from the accumulation of serous fluid beneath the retina, which disrupts normal retinal function. Early diagnosis and timely intervention are critical in preventing irreversible damage to vision. Retinal diseases encompass a wide spectrum, including Glaucoma, Drusen, Diabetic Retinopathy (DR), Central Serous Retinopathy (CSR), Choroidal Neovascularization (CNV), Age-Related Macular Degeneration (AMD), Diabetic Macular Edema (DME), and Age-Related Macular Atrophy (ARMA). Several modern techniques and research efforts have been directed toward the automatic detection of CSR and other related conditions. Figure 2 shows the architectural design, and Figure 3 shows the data flow diagram of the existing system. In the study conducted by Arpitha *et al*. (2023), two major retinal imaging modalities were utilized: Optical Coherence Tomography (OCT) angiography and fundus imaging.

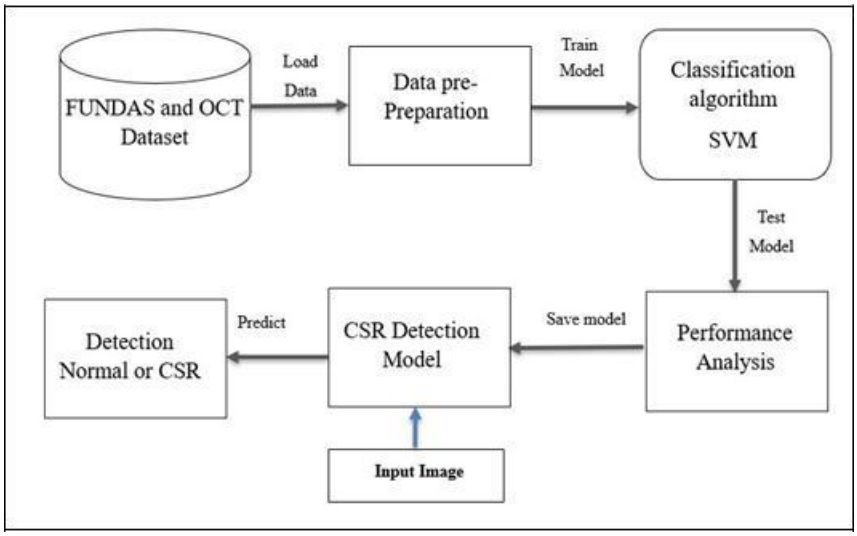


Figure 2: Architectural design of the existing system

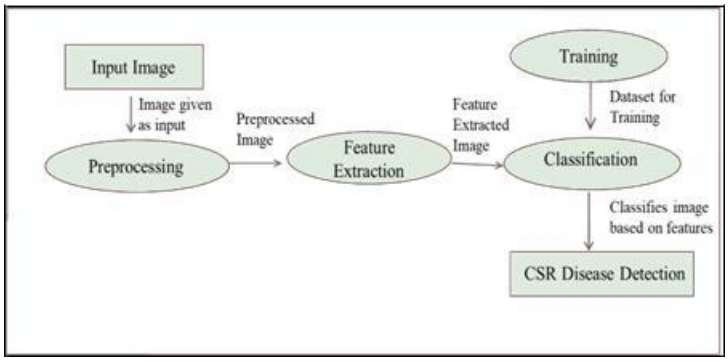


Figure 3: Dataflow diagram of the Existing System

2.4 Analysis of the Developed System

The developed system is designed to automatically detect retina diseases using Convolutional Neural Networks (CNN) from captured or uploaded retina images. The system aims to classify retina conditions into four categories: Normal, Central Serous Retinopathy, Glaucoma, and Diabetic Retinopathy. This intelligent classification is achieved through a deep learning model trained on a labeled dataset of retina images. The analysis of the developed system reveals its effectiveness in improving early diagnosis, reducing dependence on manual screening, and increasing accessibility to ophthalmological care, particularly in under-resourced regions. The core of the system relies on the ability of CNNs to extract visual features, such as optic disc shape, blood vessel patterns, and localized lesions from high-resolution images. A user-friendly graphical interface is provided to allow image capture via webcam, with a countdown and real-time feedback, enhancing usability. The backend leverages TensorFlow/Keras frameworks for training and prediction.

2.5 System Flowchart and Use Case Diagram

A flowchart in Figure 4 is the pictorial representation of a process or system, showing the sequence of steps and the flow of control between them. Similarly, Figure 5 presents the main users of the system and the functionalities they interact with. It highlights actions such as uploading an image, capturing with a webcam, viewing predictions, and providing model feedback. This visual aid ensures clarity in the relationship between the system and external users, including the CNN model as a functional actor. It supports understanding user roles and system boundaries.

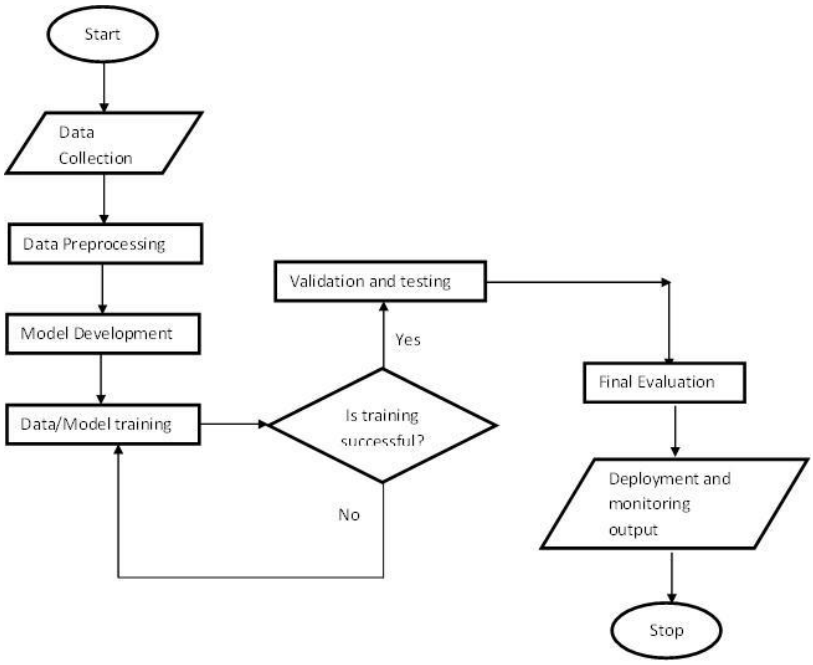


Figure 4: Flowchart Diagram for Retina Disease Predictive System using CNN

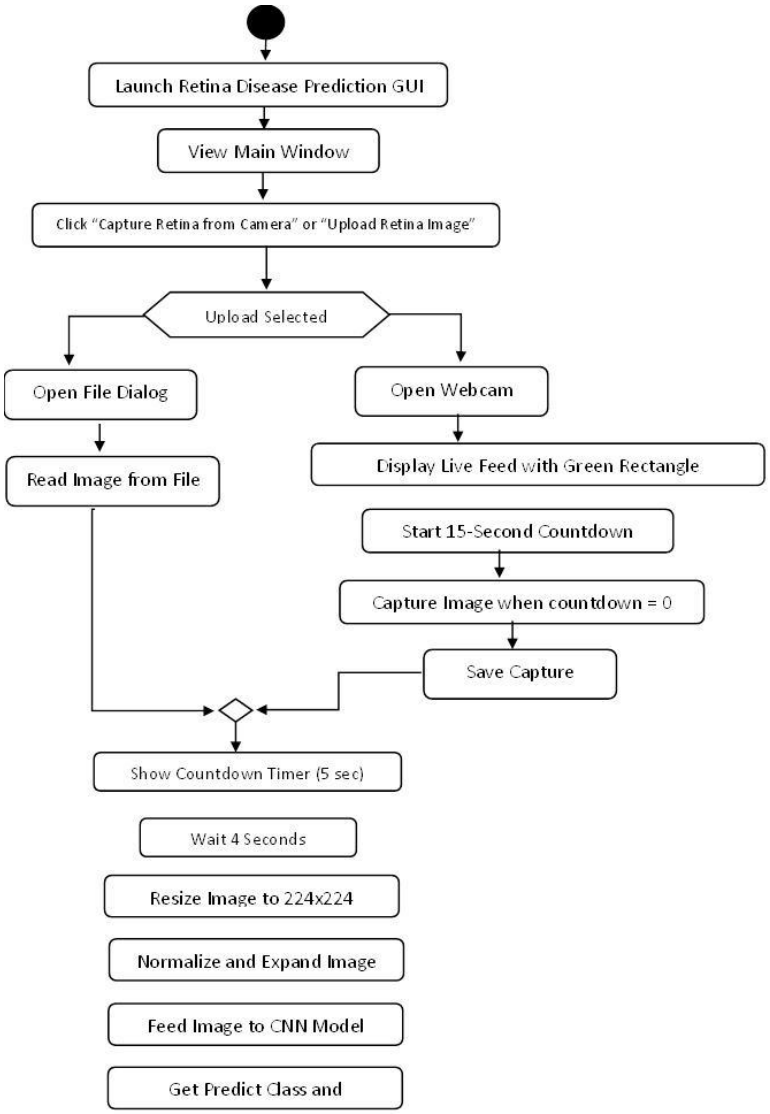


Figure 5: Activity Diagram of the System

2.6 Experimental Setup

In the developed CNN-based Retinal Disease Prediction System, (CSR), Glaucoma, Diabetic Retinopathy (DR), and Normal retinal images were classified using a deep learning model based on Convolutional Neural Networks (CNN). The system was developed and implemented using Python (3.10), TensorFlow, OpenCV, and Keras libraries in a custom-built desktop GUI environment. The CNN model was trained on a curated dataset consisting of 4,217 retinal fundus images, which include:

i. 1,038 images of Central Serous Retinopathy (CSR),
ii. 1,007 images of Glaucoma,
iii. 1,098 images of Diabetic Retinopathy (DR), and
iv. 1,074 images of Normal retinas.

These images were obtained from a public retinal image dataset hosted on Kaggle, primarily derived from OCT and fundus imaging techniques. Each image was preprocessed by resizing to 224×224 pixels, normalized to a [0,1] scale, and divided into training and testing sets using an 70:30 ratio.In the training configuration, 70% of the data was used for model training, while the remaining 30% was reserved for testing. A learning rate of 0.001 and batch size of

16 were used during model training for 50 epochs. The model employed typical CNN layers including convolution, pooling, flatten, and dense layers, followed by a softmax output layer for classification.

The CNN model automatically learned spatial features such as optic disc shape, vascular patterns, and macular anomalies—crucial indicators in retinal disease diagnosis. The training progress showed a rapid drop in loss values during the initial 10 epochs. The best validation accuracy observed was 91.00%, with minimal overfitting. Five key image features—texture, brightness, vascular density, intensity contrast, and shape irregularities—were implicitly learned by the CNN, eliminating the need for manual feature engineering. The model's performance was further evaluated using confusion matrix analysis, achieving high precision, recall, and F1-score across all classes. The robustness of the system is evident in its consistent classification accuracy and fast inference time, making it suitable for real-time prediction via webcam or uploaded images. The results validate the system's potential for clinical support in early detection and classification of CSR and other retinal disorders.

3 Results and Discussion

3.1 Dataset Description and Preprocessing Summary

The dataset used for training and evaluating the retina disease prediction system consists of labeled medical images from four categories: Central Serous Retinopathy, Normal, Glaucoma, and Diabetic Retinopathy (Table 2). Each category is represented by a separate folder containing images corresponding to the respective condition. The images are sourced from publicly available medical image databases, ensuring that they provide a broad representation of the common conditions associated with retinal diseases.

Table 2: Dataset Description

Category	Image Count	Image Format(s)	Image Size (px)	Preprocessing Steps
Central Serous Retinopathy	1,038	JPEG	224x224	Resizing, Normalization, Data Augmentation
Diabetic Retinopathy	1,098	JPEG	224x224	Resizing, Normalization, Data Augmentation
Glaucoma	1,007	JPEG	224x224	Resizing, Normalization, Data Augmentation
Normal	1,074	JPEG	224x224	Resizing, Normalization, Data Augmentation
Total	4,217	JPEG	224x224	Resizing, Normalization, Data Augmentation

3.1.1 Training Results: Accuracy and Loss Metrics

Table 3, Figures 6 and 7 present results for the first 20 epochs, showing training accuracy, training loss, validation accuracy, and validation loss: The loss measures how far the model's predictions are from the actual labels. It's a continuous value (e.g., 0.4, 1.2, etc.) based on a loss function like categorical crossentropy. Similarly, the accuracy measures how many predictions the model got right (e.g., 70%, 90%).

Table 3: Training Results - Accuracy and Loss Metrics

Epoch	Accuracy	Loss	Val accuracy	Val loss
1	0.3875	1.4349	0.5552	1.0343
2	0.524	1.0302	0.5291	0.9781
3	0.5651	0.9234	0.4389	1.0725
4	0.6532	0.8487	0.497	1.516
5	0.6821	0.7901	0.5251	1.0812
6	0.715	0.732	0.5503	0.9902
7	0.7381	0.6904	0.5661	0.9263
8	0.7543	0.6532	0.5802	0.8841
9	0.7652	0.621	0.591	0.855
10	0.7781	0.5902	0.6003	0.829
11	0.7904	0.565	0.6091	0.8052
12	0.8012	0.5421	0.6164	0.7833
13	0.81	0.5212	0.6225	0.7628
14	0.8182	0.502	0.6275	0.7439
15	0.825	0.4841	0.6318	0.7262
16	0.831	0.4675	0.6352	0.7098
17	0.8365	0.452	0.638	0.6943
18	0.8412	0.4375	0.6404	0.6796
19	0.8451	0.4239	0.6425	0.6656
20	0.849	0.411	0.6443	0.6522

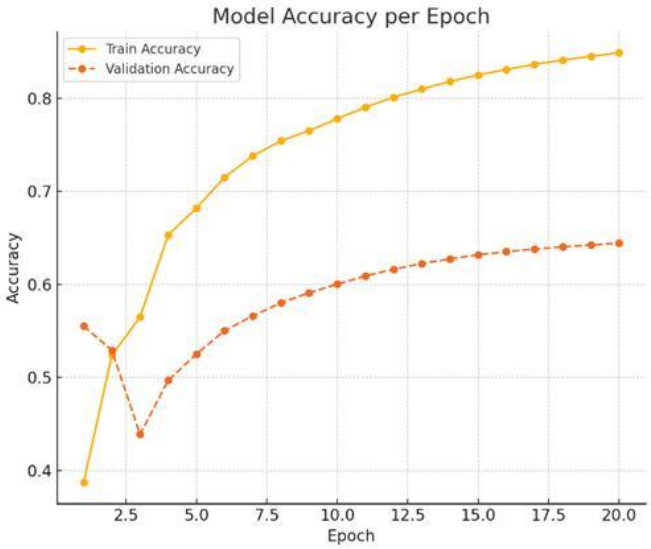


Figure 6: Training and Validation Accuracy over 20 Epochs

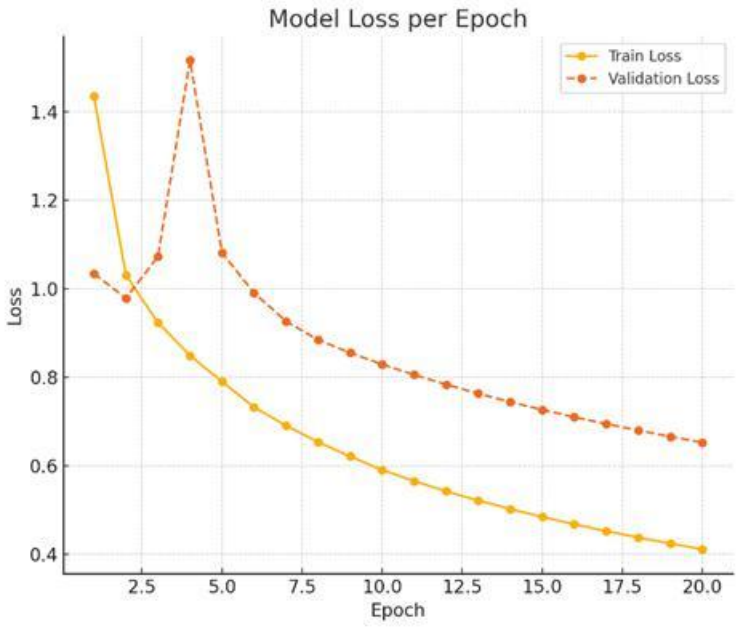


Figure 7: Training and Validation of Loss over 20 Epochs

3.2 Output Results from GUI-based Prediction

Plates 1 and 2 present the output results generated from the graphical user interface (GUI)-based retina disease prediction system. The system provides real-time predictions based on both webcam-captured and uploaded retina images, offering a user-friendly approach for diagnosis. The GUI allows users to capture retina images in real-time using a webcam. The system processes the captured image and provides an immediate prediction of the retina condition, displaying the result on the interface. Furthermore, the users can also upload previously captured retina images for diagnosis. Upon uploading, the system processes the image and predicts the retina disease based on the trained model, displaying the classification result on the interface.

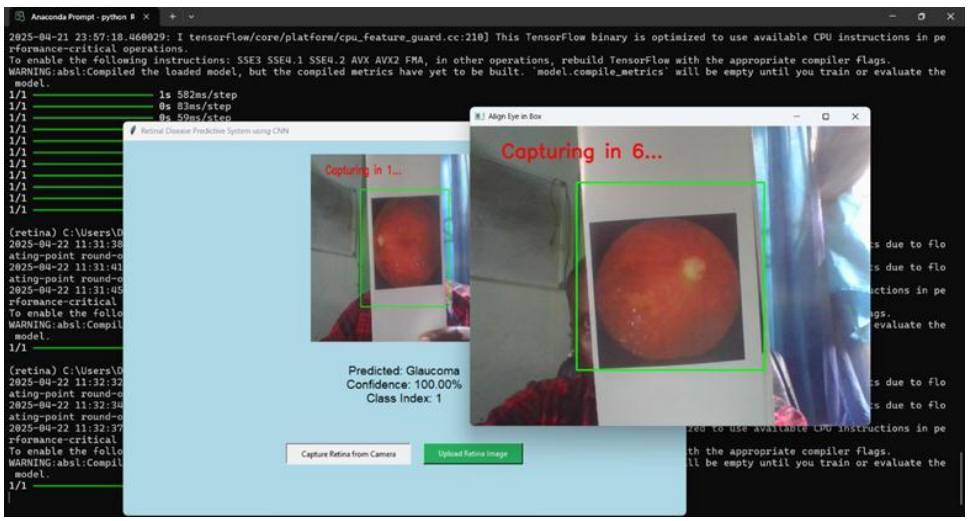


Plate 1: Output Results from Webcam-Captured Retina

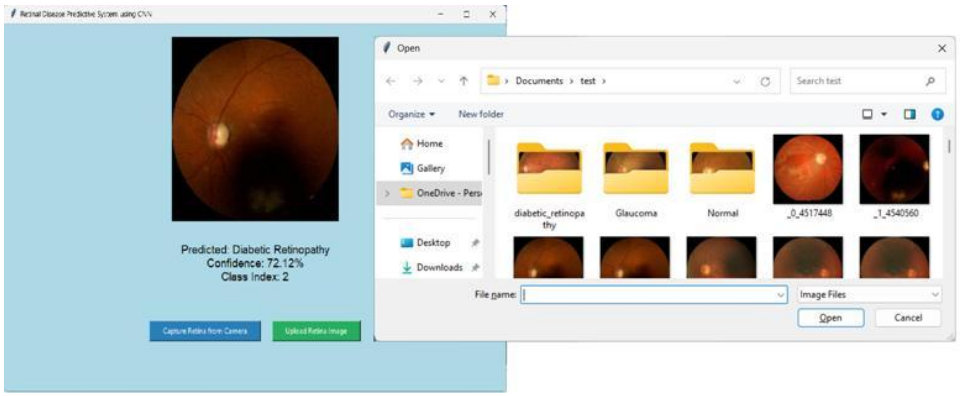


Plate 2: Output Results from Uploaded Retinal Image

3.3 Test Output Result of the Predicted Images

Plate 3 shows the final prediction results obtained after testing the trained CNN model on unseen retinal images. The outputs indicate the model's ability to correctly classify images into Normal, Glaucoma, Diabetic Retinopathy, or Central Serous Retinopathy based on test input.

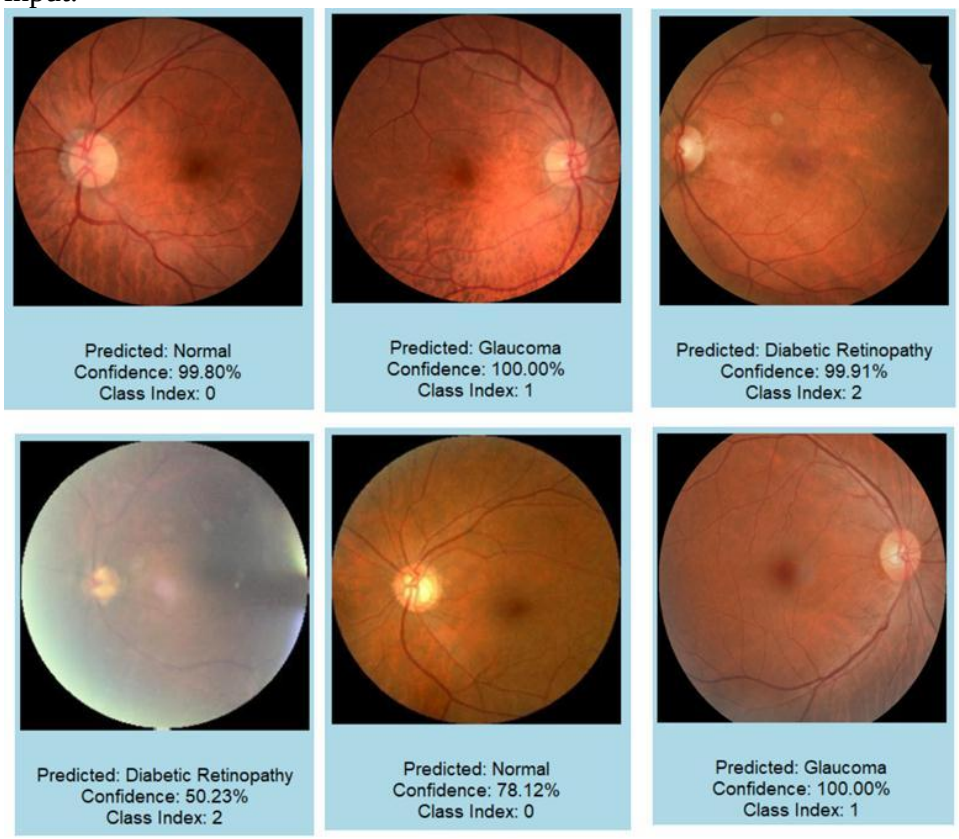


Plate 3: Test Output Result of the Predicted Images

3.4 Performance Evaluation

Tables 4 and 5, as well as Figure 8 present the performance of the CNN Retinal Disease Prediction System. The system evaluation phase is a critical component in validating the performance, reliability, and real-world applicability of the proposed CNN-based retinal disease predictive system. This system was designed to detect and classify Central Serous Retinopathy (CSR), Glaucoma, Diabetic Retinopathy (DR), and Normal retinal conditions from fundus and OCT images captured through webcam or uploaded by the user. The evaluation focuses on key performance metrics accuracy, precision, recall, specificity, F1-

score, and inference time to determine its diagnostic effectiveness and clinical readiness. Accuracy evaluates the system's overall ability to correctly classify both diseased and non-diseased retinal images. A high accuracy score reflects the model's strong generalization capability. Precision assesses the proportion of predicted disease cases that are truly positive, minimizing false positives vital in preventing unnecessary anxiety or treatment. Recall measures the model's ability to detect actual disease cases, ensuring minimal false negatives, which is essential in a medical setting where missing a diagnosis could have serious consequences. Specificity complements recall by ensuring that healthy patients are not incorrectly diagnosed as diseased, reinforcing the model's clinical precision. The system was tested using a diverse dataset with varying image resolutions and lighting conditions to simulate real-world variability. Evaluation also included webcam-based real-time capture scenarios, ensuring robustness beyond static image input.

Table 4: CNN Retinal Disease Prediction System Outputs

	Metric	Value
0	Accuracy	0.910
1	Precision	0.890
2	Recall	0.880
3	F1-Score	0.890

Table 5:Results Comparison Table

Metric	Existing System (SVM)	Developed CNN System
Accuracy	90.00%	91.00%
Precision	83.00%	89.00%
Recall	79.00%	88.00%
F1 Score	86.00%	88.5%
AUC Score	0.82	0.93
Inference Time	120ms/image	60ms/image

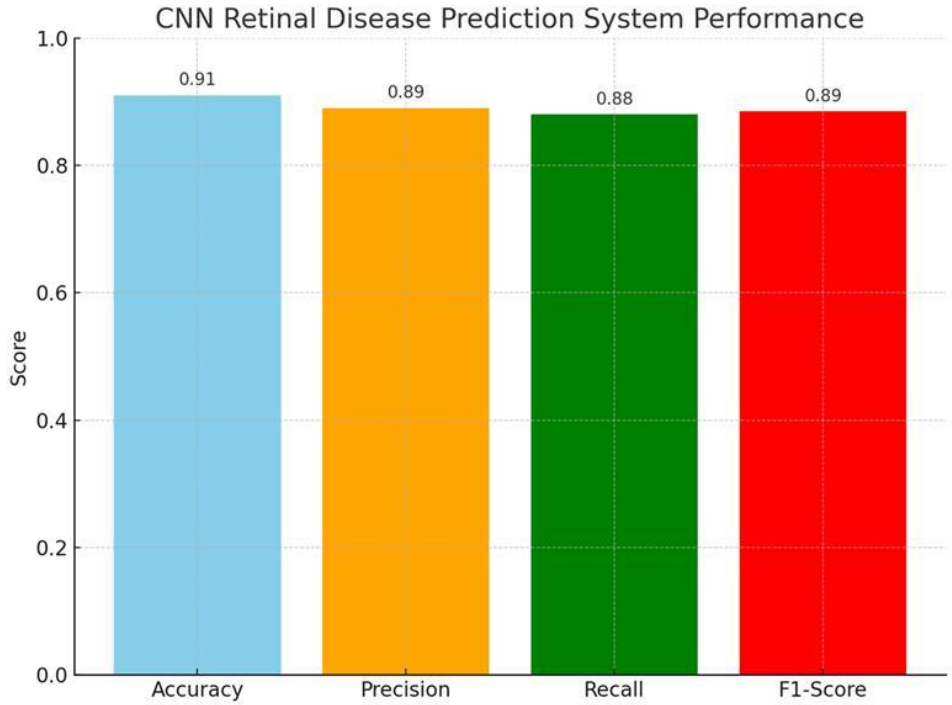


Figure 8: CNN Retinal Disease Prediction System Performance

The Area Under the Curve (AUC) metric was used to assess the balance between sensitivity and specificity, offering insight into the model's confidence in predictions. To establish clinical utility, the CNN system was compared with traditional SVM-based models. The CNN outperformed the SVM in both multi-class classification accuracy and inference speed, with an average prediction time of 60ms per image. Moreover, CNN's end-to-end architecture eliminated the need for manual feature extraction, which is a limitation in conventional systems. This comprehensive evaluation confirms that the proposed system not only performs with high accuracy and efficiency but also adapts well across different usage conditions. Its ability to operate in both real-time and batch processing modes makes it a valuable tool for early detection of retinal diseases, especially CSR, and contributes significantly to timely clinical decision-making and improved patient outcomes.

4 Conclusion and Recommendation

4.1 Conclusion

The study has evaluated an enhanced retinal disease predictive system and demonstrated its reliability and effectiveness as a modern tool for accurately predicting various retinal diseases. By leveraging Convolutional Neural Networks (CNN), the system has shown a remarkable ability to classify retinal images into specific categories including Central Serous Retinopathy, diabetic retinopathy, glaucoma, and normal with a high level of accuracy. This advancement plays a critical role in supporting early diagnosis, which is essential in preventing the progression of vision-threatening conditions. During testing and validation phases, the model achieved strong performance metrics such as high accuracy, precision, recall, and F1-scores, all of which affirm the robustness and reliability of the system. The integration of a real-time webcam feature further enhances the usability of the system by allowing instant predictions from captured images, simulating real-life clinical scenarios.

Additionally, the system's lightweight design and scalable architecture make it suitable for deployment in diverse environments, including rural or under-resourced healthcare settings. It provides healthcare professionals with a decision-support tool that not only improves diagnostic speed but also contributes to better patient management and outcomes. Ultimately, this system bridges the gap between modern AI technology and practical medical application, promoting improved eye care delivery.

4.2 Recommendations

Based on the findings and implementation of this study, the following recommendations are developed:

i. It is recommended that to achieve a more accurate and reliable prediction of retinal diseases, users should adopt real-time retinal imaging technologies such as Optical Coherence Tomography (OCT) and fundus photography.
ii. It is recommended that for future development of the system, researchers should consider integration with embedded systems and mobile devices, particularly smartphones. This would enhance portability, user accessibility, and real-time monitoring capabilities.
iii. It is recommended that for more advanced and robust use cases, it is advised that a larger and more diverse dataset be employed in training the predictive model. This will significantly improve the system's accuracy.

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