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AUREVA: An AI-Driven Multimodal Framework for Reliable Eye Disease Screening with Uncertainty Estimation

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Abstract

Eye diseases such as Conjunctivites, Uveitis, Cataract and other external eye disorders often remain diagnosed in their early stages due to limited access to ophthalmologists, language barriers and lack of awareness about symptoms. Early detection of eye diseases plays a crucial role in preventing vision impairment and blindness. Recent advancements in Artificial Intelligence have enabled automated eye disease screening using image-based and symptom-based approach. However, most existing systems rely on single-modal inputs and provides deterministic predictions without explaining model confidence, which limits their reliability and user trust in clinical things. Real-world deployment remains challenging due to limited transparency, confidence estimation, and accessibility. Language and interaction barriers remain underexplored, particularly in multilingual and low-resource settings. The proposed approach aims to improve accessibility, reliability, and early detection of eye diseases, making it suitable for deployment in remote healthcare environments.

Keywords: Artificial Intelligence; Eye Disease Detection; Telemedicine; Multimodal Diagnosis; Explainable AI; Ophthalmology.

How to Cite This Article

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Introduction

In recent years, Artificial Intelligence has achieved significant advances, driven by continuous improvements in Machine Learning methods. Among these advances Deep Learning has emerged as the most transformative branch of Machine Learning, delivering unprecedented breakthroughs in diagnosis ans treatment. Medical Imaging (MI) is a cornerstone of modern healthcare, providing clinical insights for the diagnosing, treating and monitoring various diseases.

Eye diseases such as cataract, glaucoma, and diabetic retinopathy are among the leading causes of vision loss worldwide. Early detection plays a crucial role in preventing permanent damage, yet access to specialized healthcare remains limited in many regions.

With the rise of artificial intelligence, automated diagnostic systems have gained attention. However, most existing solutions rely only on image-based analysis, ignoring important contextual information such as patient symptoms. Moreover, lack of transparency in AI decisions reduces trust among healthcare professionals.

To address these challenges, this research introduces AUREVA, a multimodal AI framework that combines:

- Image-based disease detection
- Symptom-based analysis
- Explainable AI
- Telemedicine integration

This system is designed to provide accurate, interpretable, and accessible eye disease screening, especially for underserved populations.Overall, the proposed framework aims to improve early disease detection, increase accessibility to eye care services, and promote safe, transparent, and efficient AI-assisted ophthalmic diagnosis, particularly for underserved populations.

Literature Review

The application of Artificial Intelligence (AI) in ophthalmology has witnessed significant growth in recent years, particularly in the area of automated eye disease detection. Deep learning techniques, especially Convolutional Neural Networks (CNNs), have demonstrated high effectiveness in analyzing ocular images and identifying various eye conditions such as diabetic retinopathy, glaucoma, and cataract [1]. These models are capable of learning complex visual patterns from large datasets, enabling accurate and efficient disease classification.

Several studies have explored the use of AI for large-scale ophthalmic screening. For instance, deep learning-based systems have been successfully developed for detecting diabetic retinopathy from retinal fundus images with performance comparable to clinical experts [2]. These systems highlight the potential of AI in reducing diagnostic workload and improving screening efficiency. However, most of these approaches rely exclusively on image-based inputs and do not consider additional clinical information such as patient-reported symptoms [3].

In the context of telemedicine, AI-driven diagnostic systems have been integrated into remote healthcare platforms to enable early detection and consultation. Tele-ophthalmology solutions allow patients to upload eye images and receive preliminary assessments without visiting a healthcare facility. While these systems improve accessibility, they often lack advanced features such as interpretability and confidence evaluation, which are essential for reliable clinical use.

Recent research has also focused on the use of Natural Language Processing (NLP) for analyzing clinical text data. NLP techniques enable the extraction of meaningful information from patient-reported symptoms, medical records, and diagnostic notes. Although these approaches provide valuable insights, they are typically used independently and are rarely integrated with image-based models in ophthalmic applications.

Overall, the existing literature primarily focuses on single-modality approaches, either image-based or text-based, with limited emphasis on integrating multiple data sources. Furthermore, many systems lack interpretability and mechanisms for assessing prediction reliability. To address these gaps, the proposed AUREVA framework introduces a multimodal approach that combines image analysis and symptom-based evaluation, along with explainable AI and uncertainty estimation, to provide a more accurate, transparent, and reliable solution for eye disease detection.

Artificial Intelligence (AI) and Machine Learning (ML) are rapidly transforming ophthalmology by enabling early disease detection, improving diagnostic accuracy, and expanding access to eye care through digital platforms. These technologies function as intelligent decision-support systems that assist clinicians in identifying ocular diseases while enhancing overall patient outcomes [1], [2].

Automated Ocular Image Analysis

One of the most significant applications of AI in ophthalmology is the automated analysis of ocular images. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in detecting retinal and anterior eye abnormalities. These models are capable of identifying diseases such as diabetic retinopathy, glaucoma, cataract, and age-related macular degeneration with accuracy comparable to clinical experts [1]–[4]. By learning complex visual patterns from large annotated datasets, CNN-based systems enable faster diagnosis and reduce the burden on healthcare professionals.

Virtual and Immersive Eye Care Environments

Recent advancements in digital health technologies have introduced virtual and immersive environments for ophthalmic care. Interactive visualization tools, including 3D ocular models, assist clinicians in explaining complex conditions to patients. Additionally, AI-based eye-tracking systems can analyze visual behavior patterns to support the detection of neurological and vision-related disorders, thereby enhancing diagnostic capabilities [12], [14].

Mobile Health Applications for Self-Screening

Mobile health (mHealth) applications equipped with AI algorithms enable users to perform preliminary eye assessments using smartphones. These applications support tests such as visual acuity, color vision, and contrast sensitivity, providing instant feedback and recommendations for further consultation. Such tools promote early detection and increase patient awareness, contributing to preventive healthcare practices [10], [11].

Real-World Implementations

Several AI-based diagnostic systems have already been deployed in real-world clinical settings. Autonomous AI models have demonstrated the capability to detect diabetic retinopathy directly from retinal images without specialist intervention [1]. Additionally, AI-driven imaging systems are being utilized for glaucoma detection by analyzing structural changes in the optic nerve, highlighting the practical applicability of AI in ophthalmology [4].

Challenges and Ethical Considerations

Despite significant progress, the deployment of AI in healthcare presents challenges related to data privacy, algorithmic bias, and unequal access to digital technologies. Ensuring transparency, fairness, and security in AI systems is critical for their ethical adoption. Moreover, AI solutions are intended to augment clinical decision-making rather than replace professional medical expertise [18], [20].

Future Directions

Emerging technologies are expected to further enhance AI-assisted ophthalmic care. Innovations such as wearable ocular sensors, smart contact lenses for intraocular pressure monitoring, cloud-based diagnostic systems, and secure data-sharing frameworks are gaining attention. These advancements, combined with telemedicine and multimodal AI integration, have the potential to significantly improve early detection, accessibility, and management of eye diseases on a global scale [21]–[24]

System Architecture

The proposed framework is designed as a telemedicine-oriented multimodal system that enables automated screening of eye diseases along with preliminary therapeutic recommendations. The architecture combines image analysis, symptom interpretation, and explainable artificial intelligence techniques to assist in early diagnosis. By integrating multiple computational components, the system aims to support remote healthcare environments where ophthalmology specialists may not be easily

The AUREVA framework is designed as a modular and scalable system that integrates multiple computational components to perform multimodal analysis. The architecture follows a structured pipeline that transforms raw input data into meaningful diagnostic insights.

The system begins with a data acquisition module, where users provide ocular images and textual descriptions of symptoms. These inputs are preprocessed to ensure consistency and compatibility with machine learning models. Image preprocessing includes resizing, normalization, and augmentation, while textual data undergoes tokenization and vectorization.

The processed image is passed through a deep learning model based on MobileNetV2, which extracts high-level visual features relevant to different eye diseases. Simultaneously, the symptom data is processed using NLP techniques to generate structured feature representations.

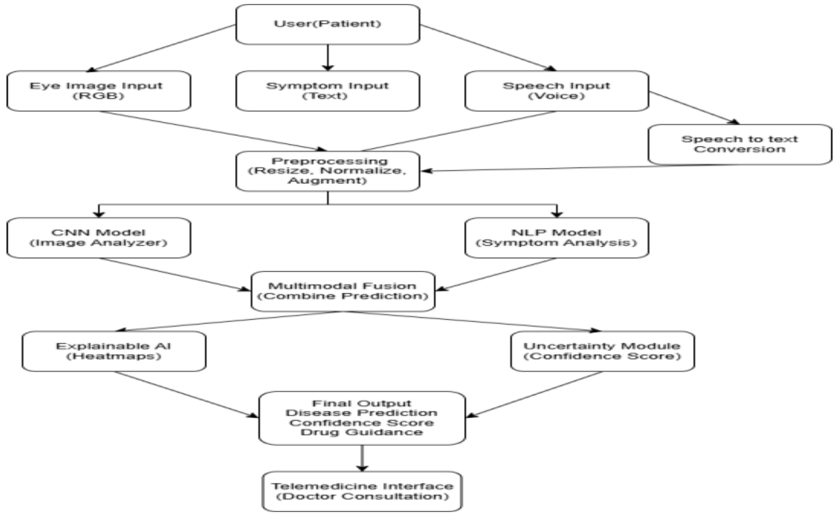


Fig. 1. *Workflow of AUREVA-Based Multimodal Eye Disease Screening System*

Data Acquisition Layer

The initial stage of the system focuses on collecting patient information through a remote telemedicine interface. Users can upload ocular images such as fundus photographs or anterior eye images, while simultaneously entering textual descriptions of symptoms experienced by the patient. This multimodal data collection strategy provides richer clinical context compared to traditional systems that rely only on image data.

Prior to analysis, both visual and textual inputs undergo preprocessing procedures to ensure compatibility with machine learning algorithms. Image preprocessing includes resizing, normalization, and augmentation operations such as rotation and illumination adjustments to improve model robustness. Textual symptom descriptions are processed through noise removal, tokenization, and feature transformation to convert unstructured natural language into structured representations suitable for computational analysis.

Mathematical Model

The proposed system can be mathematically represented as a multimodal classification framework that processes both image and textual inputs

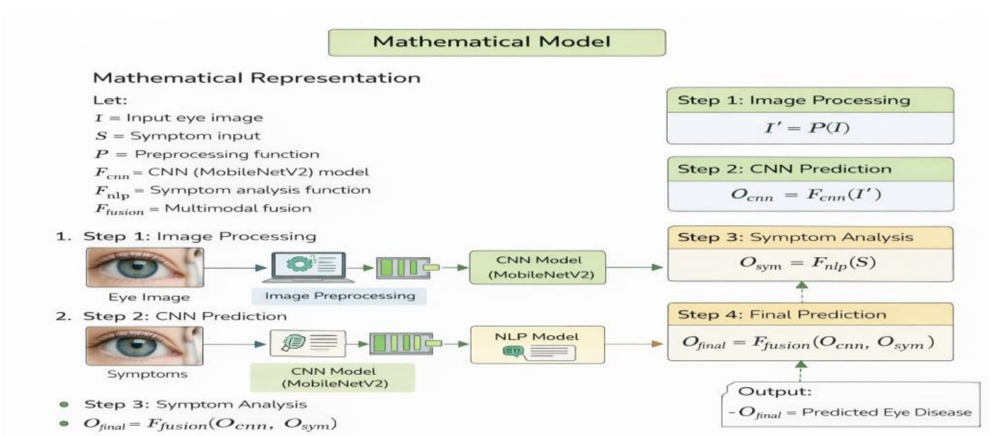


Fig. 2. *Mathematical Representation of Multimodal Eye Disease Diagnosis Framework*

Let $\boldsymbol{I}$ denote the input image and $\boldsymbol{T}$ represent the symptom text. Feature extraction is performed separately for each modality. The image feature vector is obtained using a deep learning model:

$F_i = f_\theta(I)$

where f_θ represents the CNN model parameters.

Similarly, the textual feature vector is obtained using an NLP function:

$F_T = g_\phi(T)$

The extracted features are combined using a fusion function:

$F = \alpha F_I + \beta F_T$

where α and β are weighing coefficients.

The final classification is performed using a softma function:

$P(Y=i) = e^{z_i} / \Sigma e^{z_j}$

The model is trained using cross-entropy loss:

$L = - \Sigma y \log(\hat{y})$

To ensure reliability, uncertainty is estimated using entropy:

$U = - \Sigma P(Y_i) \log P(Y_i)$

This mathematical formulation enables the system to perform accurate, interpretable, and confidence-aware predictions.

Dataset and Data Preprocessing

Dataset Sources

The performance of the proposed AI-based eye disease detection system depends significantly on the quality and diversity of the image dataset used for training and evaluation. In this study, a dataset of ocular images was compiled from publicly available repositories containing labeled samples of common eye diseases.

The dataset includes images corresponding to multiple ocular conditions such as diabetic retinopathy, glaucoma, cataract, and conjunctivitis, along with normal eye images for comparison. These datasets consist of pre-collected clinical images rather than real-time captured data, ensuring consistency and availability for model training and testing.

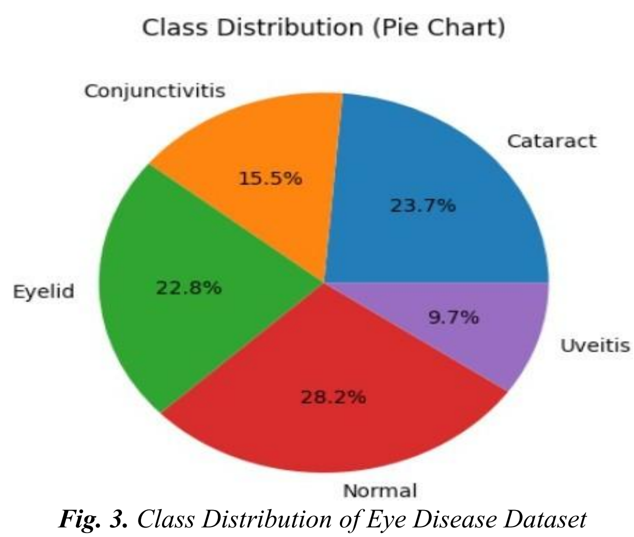


***Fig. 3.** Class Distribution of Eye Disease Dataset*

All images in the dataset are standard color (RGB) images, as commonly obtained from digital cameras and clinical imaging devices. Using RGB images allows the model to capture important visual features such as color variations, redness, and texture patterns, which are essential for identifying different eye conditions.

Uncertainty Estimation in AI-Based Diagnosis

Artificial intelligence models applied in medical diagnosis generate predictions based on patterns learned from training data. However, in practical healthcare environments, predictions may involve uncertainty due to limited datasets, overlapping symptoms among diseases, or variations in patient conditions. Recognizing this uncertainty is important in clinical applications to prevent incorrect automated decisions. Therefore, the proposed framework incorporates an uncertainty estimation component to evaluate the reliability of model predictions.

The goal of uncertainty estimation is to quantify the confidence associated with each prediction generated by the AI model. Instead of providing only a disease classification, the system also outputs a confidence score indicating how strongly the model supports the predicted result.

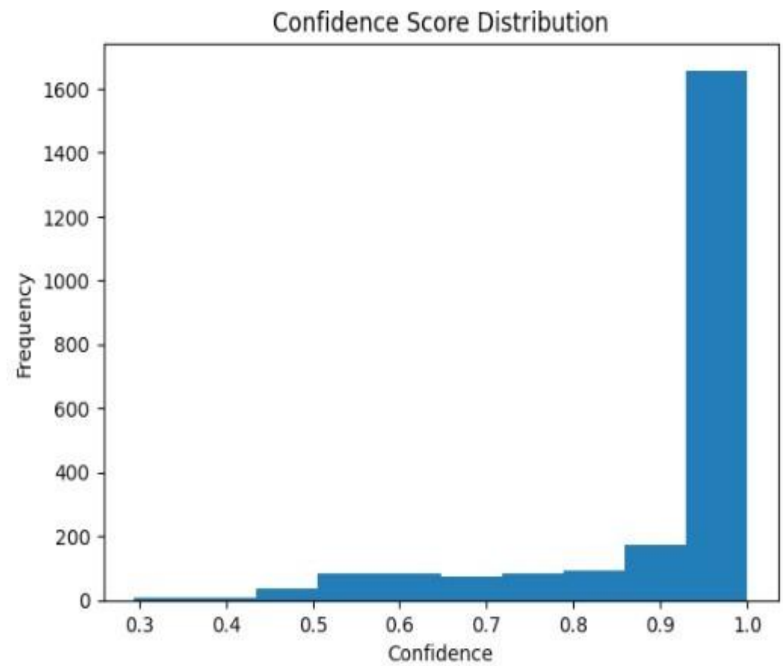
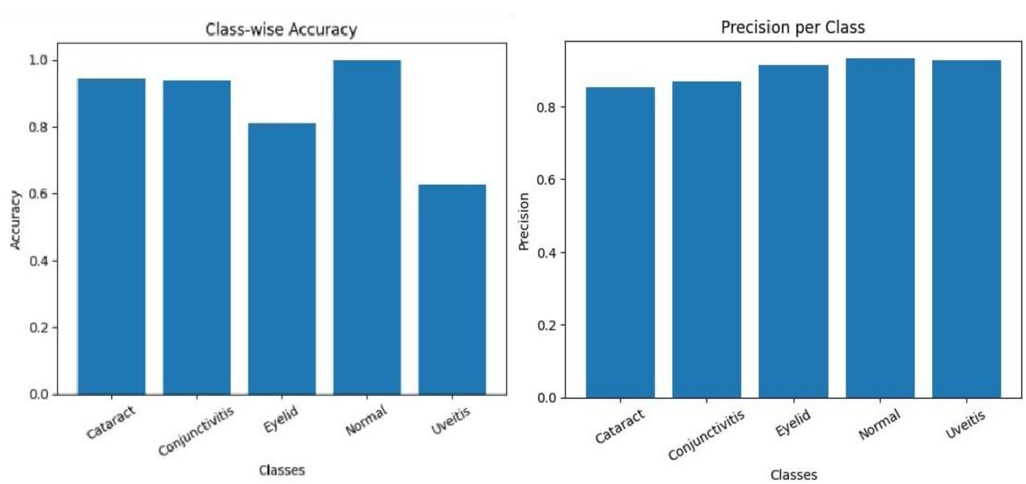


Fig. 4. *Distribution of Prediction Confidence Scores Across Test Samples*Confidence Score Evaluation

In the proposed system, the trained machine learning model produces probability values for each possible disease category. These probabilities indicate the likelihood that a patient belongs to a specific class based on the provided clinical features and symptoms. The class with the highest probability is considered the predicted outcome, and its probability value represents the confidence level of the model. For example, a prediction of diabetic retinopathy with a probability of 0.92 reflects high confidence, whereas a probability closer to 0.50 suggests a more uncertain decision.



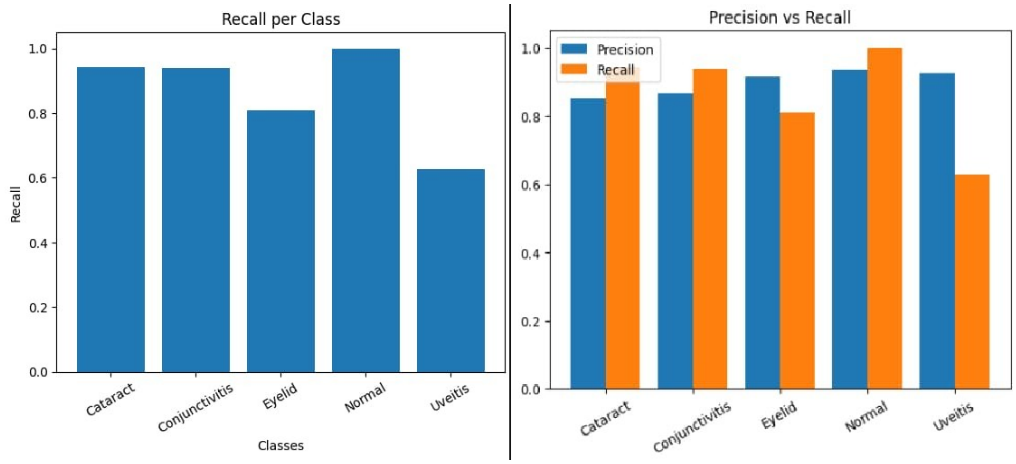


Fig. 5. Class-Wise Performance Evaluation of the Proposed Eye Disease Screening Framework

Prediction Probability Analysis

The probability distribution across disease classes is further analyzed to assess prediction reliability. When the difference between the highest probability and other class probabilities is small, the model may be uncertain about the final classification. In such cases, the system identifies the output as a low-confidence prediction. This mechanism helps prevent overly confident conclusions in situations where clinical indicators are ambiguous.

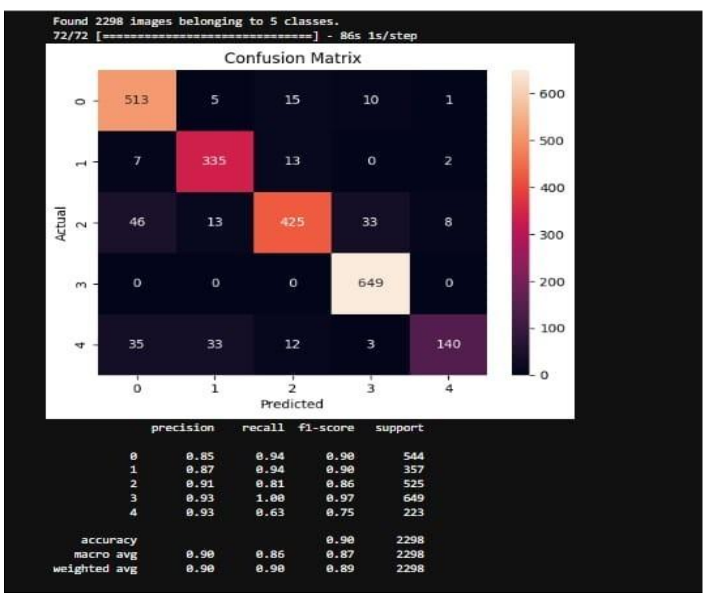


Fig. 6. Classification Performance Assessment of the Proposed AUREVA Framework

Advantages of the Proposed System

The proposed AUREVA framework provides several advantages compared with conventional eye disease screening methods and existing AI-based diagnostic systems. By combining artificial intelligence with telemedicine technologies, the system improves accessibility, diagnostic efficiency, and early disease identification.

One key advantage of the proposed framework is its ability to support early detection of eye diseases. Timely identification of conditions such as glaucoma, cataract, and diabetic retinopathy is essential for preventing severe vision impairment. By analyzing patient health indicators and symptom-related attributes using machine learning techniques, the system can identify potential disease risks at an early stage and encourage timely medical consultation.

Another important feature of the framework is its multimodal diagnostic capability. Unlike many existing approaches that rely solely on image-based analysis, the proposed system integrates structured health attributes and symptom-based information within the predictive model. This integration of multiple data sources enables a more comprehensive assessment of patient conditions and improves diagnostic reliability.

The system also leverages telemedicine technology, allowing users to access preliminary diagnostic support remotely. Patients can submit health information and symptoms without the need for an in-person hospital visit. This functionality is particularly beneficial for individuals in rural or underserved regions where specialized ophthalmic services may not be readily available.

Overall, the integration of early disease screening, multimodal data analysis, telemedicine accessibility, explainable AI mechanisms, and basic treatment guidance makes the AUREVA framework a promising approach for improving digital eye healthcare services.

Results and Discussion

The performance of the proposed system was evaluated using a dataset of ocular images and symptom data. Multiple machine learning models were implemented and compared, including CNN-based approaches, Random Forest, and Support Vector Machine (SVM).

Experimental results indicate that the multimodal approach significantly improves classification accuracy compared to single-modality systems. The integration of symptom data provides additional contextual information, reducing misclassification in visually ambiguous cases.

Among the evaluated models, Random Forest achieved the highest accuracy, while the deep learning model based on MobileNetV2 demonstrated efficient performance with lower computational cost. The use of explainable AI techniques further enhanced interpretability, allowing users to understand the reasoning behind predictions.

The inclusion of uncertainty estimation proved beneficial in identifying low-confidence predictions, thereby improving the reliability of the system. Overall, the results demonstrate the effectiveness of the proposed framework in achieving accurate and trustworthy eye disease detection.

Future Work

Future research will focus on enhancing the functionality and real-world applicability of the proposed AUREVA framework.

One important direction involves integrating large-scale clinical datasets collected from hospitals and healthcare institutions. Access to real-world patient data will enable machine learning models to learn more diverse patterns and improve prediction accuracy across different populations.

Another potential improvement is the development of a mobile-based telemedicine application that allows users to access the system through smartphones or portable devices. A mobile platform would enable patients to submit health information, describe symptoms, and receive AI-assisted diagnostic insights remotely, thereby improving accessibility in remote areas.

Future studies will also explore expanding the dataset to include additional ophthalmic disease categories and a broader range of clinical attributes. This expansion would allow the system to detect a wider range of eye disorders and improve diagnostic coverage.

Furthermore, the integration of advanced deep learning models such as Convolutional Neural Network will be investigated for analyzing ocular images. Combining image-based analysis with patient health data will further strengthen the multimodal diagnostic capability of the framework.

Additional research will also focus on enhancing explainable AI and uncertainty estimation mechanisms to provide more transparent and reliable predictions. These improvements will help clinicians better understand model decisions and identify cases requiring further medical evaluation.

Conclusion

This study presented AUREVA, an AI-based framework designed for early detection and screening of eye diseases using machine learning techniques combined with telemedicine support. The system analyzes patient health attributes and symptom-related indicators to identify potential risks associated with ocular diseases and provide preliminary diagnostic guidance.

Several machine learning algorithms were implemented and evaluated to determine the most effective predictive model. Experimental results indicated that the Random Forest classifier achieved the highest prediction accuracy among the evaluated methods, demonstrating the effectiveness of ensemble learning techniques in disease prediction tasks. The framework also incorporates multimodal diagnostic capabilities, enabling the integration of patient symptoms and clinical attributes for comprehensive disease analysis. In addition, the use of explainable AI techniques improves transparency by highlighting the factors that influence model predictions, thereby increasing trust in AI-assisted healthcare systems. Another important contribution of the system is the integration of telemedicine technology, which enables remote access to diagnostic support and health guidance. This feature improves accessibility to eye care services, particularly in regions where specialized medical facilities are limited. Furthermore, the inclusion of preliminary drug guidance and precautionary recommendations helps increase patient awareness and encourages timely medical consultation. Overall, the proposed AUREVA framework demonstrates the potential of AI-driven healthcare solutions for improving early eye disease detection, enhancing access to ophthalmic services, and supporting clinicians through intelligent decision-support systems.

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