Building an AI-Based Eye Cell Localization System

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ABSTRACT

Currently, ophthalmic medicine faces increasing demands for improved diagnostic efficiency and accuracy. The application of artificial intelligence (AI) technology offers an innovative solution to these challenges. This study leverages AI and deep learning algorithms to achieve precise localization of eye cells. By performing multi-layer processing on medical images, the system accurately delineates the contours of eye cells, enabling physicians to quickly assess patients' ocular health conditions. By integrating this system into the medical workflow, the reliance on manual identification is significantly reduced, thereby enhancing diagnostic efficiency and minimizing the risk of human error. Furthermore, the precise image analysis results assist doctors in formulating treatment plans more efficiently, providing patients with more accurate and personalized therapeutic solutions. The application of this technology extends beyond optimizing the diagnostic process, opening new possibilities for the integration of AI with medical science. In the future, such intelligent systems could be widely adopted for various medical imaging analyses, driving advancements in smart healthcare. As research progresses, this technology is expected to bring substantial improvements to ophthalmology and the broader medical field, enhancing overall healthcare quality and ensuring more comprehensive patient care.

Keywords: Medical Technology, Cell Localization, Edge Detection, Artificial Intelligence, Intelligent Healthcare

1. Introduction

With continuous advancements in medical technology and the rapid development of artificial intelligence (AI), medical imaging analysis has become a crucial tool for disease diagnosis and treatment. In the field of ophthalmology, the precise localization and identification of eye cells serve as the foundation for diagnosing various diseases. However, existing cell recognition processes present numerous challenges, including disparities in medical resource distribution and the complexity of image processing. In remote areas or regions with limited medical resources, the shortage of specialized ophthalmologists further exacerbates diagnostic inefficiencies, increasing the risk of delayed diagnoses for patients. Additionally, traditional cell recognition methods rely heavily on manual operations by physicians, which are not only time-consuming and labor-intensive but also susceptible to fatigue and subjective judgment. These factors contribute to inconsistencies in diagnostic outcomes, ultimately affecting healthcare quality. Such challenges necessitate the development of a more efficient and accurate solution to meet the growing demand for ophthalmic diagnostics.

The primary objective of this study is to develop an AI-driven intelligent eye cell localization system that can automatically analyze medical images, rapidly and accurately locate eye cells, and provide real-time analysis results for physicians to support clinical diagnosis and decision-making. By integrating deep learning and image processing techniques, the system effectively identifies key features of eye cells, reducing human error and improving diagnostic accuracy. Additionally, the system's scalable architecture allows for future applications beyond eye cell localization, extending to automated screening and diagnosis of various ophthalmic diseases, thereby providing comprehensive technical support for the advancement of smart healthcare.

In the current medical diagnostic framework, physicians often spend significant time interpreting medical images. This is particularly evident in ophthalmology, where the cell localization and analysis process is intricate, increasing the workload of doctors and affecting diagnostic efficiency. The intelligent system developed in this study automates image analysis, reducing the time physicians spend on repetitive tasks, allowing them to focus on more critical clinical decisions and patient communication. Furthermore, the system's automation accelerates the diagnostic process, significantly reducing patient wait times and ensuring a more efficient medical workflow. This is especially beneficial in high-patient-volume settings or emergency cases, where it enhances overall healthcare service efficiency.

The applicability of this technology extends beyond large medical institutions and is particularly valuable in remote areas with limited medical resources. Many regions lack specialized ophthalmologists, making it challenging to provide high-quality diagnostic and treatment services. This system can serve as an assistive tool for remote medical consultations, enabling accurate diagnostic support even in resource-constrained environments, thereby promoting more balanced medical resource distribution and reducing disparities in healthcare access between urban and rural areas. Additionally, manual diagnosis is often influenced by physicians' experience, fatigue, and subjective judgment, leading to inconsistencies in diagnostic results. The AI model used in this study is trained on a vast dataset of medical images, allowing it to learn critical diagnostic features and ensure stable and reproducible outcomes. With continuous algorithm optimization, the system can progressively improve diagnostic accuracy over time, providing physicians with more objective diagnostic support.

This research aims to address existing challenges in the healthcare system through technological innovation, enhancing both diagnostic efficiency and accuracy while laying the foundation for the future development of smart healthcare. As AI technology advances, the system could be further expanded to support the diagnosis of other ophthalmic diseases and integrated into telemedicine platforms, broadening the scope of intelligent healthcare applications. Ultimately, this innovation seeks to achieve a more precise, efficient, and accessible healthcare service for all.

The global healthcare system is facing a significant shortage of specialized ophthalmologists, a challenge that is particularly severe in remote areas and regions with limited medical resources. According to multiple medical reports, the demand for ophthalmic diagnosis is rapidly increasing due to population aging and the rising number of patients with eye diseases. However, the current number of professional ophthalmologists is insufficient to accommodate this growing trend. Ophthalmic disease diagnosis often relies on physicians conducting detailed observations and analyses of cellular images, but due to the constraints of limited human resources, many patients experience prolonged waiting times for diagnosis, potentially missing critical treatment opportunities. Additionally, disparities in medical resource distribution mean that patients in certain regions may lack access to specialized medical services, further exacerbating diagnostic delays and uncertainties.

Traditional eye cell recognition methods still primarily rely on manual operations by ophthalmologists, requiring them to examine and mark cell locations within a large volume of medical images. This is not only a tedious and highly specialized task but also demands that physicians maintain extreme sensitivity to subtle cellular changes, particularly in the early stages of disease, where diagnostic accuracy depends heavily on precise image analysis. However, this manual approach presents clear drawbacks. First, the process of manually identifying and comparing images is highly time-consuming, limiting diagnostic efficiency—especially in situations where there is a shortage of trained professionals. Second, the intensive nature of this work imposes significant psychological and physical burdens on physicians, and prolonged manual analysis can lead to fatigue, which affects diagnostic accuracy. Furthermore, as manual diagnosis depends on individual expertise and subjective judgment, inconsistencies in results are inevitable, posing a challenge to maintaining high medical quality standards.

Given these challenges, the implementation of an automated and intelligent eye cell localization system has become an urgent necessity. With advancements in artificial intelligence and deep learning technologies, it is now possible to develop an automated system designed for high efficiency and accuracy, replacing traditional manual operations. This system can rapidly identify cell locations using advanced image processing techniques and improve recognition precision through deep learning models trained on large-scale medical datasets. Automated diagnosis not only alleviates the workload of physicians and reduces stress associated with repetitive tasks but also ensures the consistency and reliability of diagnostic results. Additionally, the application of intelligent systems significantly shortens diagnostic turnaround times, enabling patients to receive accurate diagnoses more quickly, thereby accelerating treatment decision-making and improving overall healthcare service efficiency.

As AI technology continues to advance, such systems can be further expanded into telemedicine applications, assisting hospitals and clinics in resource-limited regions by providing more precise diagnostic support. Ultimately, the integration of AI-driven diagnostic tools contributes to the creation of a more equitable, efficient, and accessible healthcare system, ensuring that patients, regardless of location, can receive timely and high-quality ophthalmic care.

Ophthalmologists rely on eye cell localization maps because they provide critical clinical insights for diagnosing and treating various eye diseases. The human eye consists of intricate structures, including retinal ganglion cells, photoreceptor cells (cones and rods), and other specialized cellular layers. The position and distribution of these cells directly affect visual function. By analyzing these maps, doctors can detect abnormalities such as cell damage, apoptosis, or disorganization, enabling early diagnosis and more effective treatment of ophthalmic diseases. Eye cell localization maps play a crucial role in diagnosing various conditions. For example, in age-related macular degeneration (AMD), changes in the distribution of retinal cells within the macular region can indicate disease progression before symptoms become severe. Diabetic retinopathy affects retinal cells and microvascular structures, and early-stage lesions can be identified using localization maps, allowing timely intervention. Similarly, retinitis pigmentosa (RP) leads to photoreceptor cell degeneration, and these maps help track the progression of cell loss, which is essential for managing long-term care. Since many ophthalmic diseases develop gradually, long-term monitoring is essential to assess treatment effectiveness. By comparing sequential localization maps, ophthalmologists can observe changes in cell density and distribution, evaluate whether a treatment plan is working, and determine if the disease is worsening or stabilizing. This proactive tracking is particularly crucial for chronic eye diseases, where early detection of subtle cellular changes enables doctors to adjust treatment strategies before significant vision loss occurs. Beyond diagnosis and disease monitoring, localization maps are also valuable for precision treatment and targeted therapy. Many advanced ophthalmic treatments require precise targeting to maximize therapeutic efficacy while minimizing damage to surrounding healthy tissues. Optical coherence tomography (OCT) provides high-resolution imaging that helps pinpoint optimal treatment areas. In retinal drug injections, localization maps guide physicians to ensure medication is delivered precisely to affected regions, reducing the risk of unintended damage. This level of precision significantly enhances both treatment safety and patient outcomes. In addition to their clinical applications, eye cell localization maps are valuable for research and technological advancements. By analyzing large-scale localization datasets, researchers can identify new disease patterns and better understand the mechanisms behind retinal disorders. These datasets also contribute to the development of artificial intelligence (AI) models for medical imaging analysis. As deep learning and image processing techniques evolve, AI-powered localization systems will be able to automatically analyze images, provide preliminary diagnostic insights, and reduce the workload of ophthalmologists. This automation will improve diagnostic efficiency, enhance accuracy, and ensure more patients receive timely and precise diagnoses. Eye cell localization maps serve as essential tools for ophthalmologists, allowing for accurate disease diagnosis, continuous disease monitoring, and optimized treatment planning. With advancements in AI and medical imaging, these maps will become even more precise and widely used, improving ophthalmic healthcare. As a result, more patients will benefit from cutting-edge diagnostic and treatment solutions, ultimately leading to better visual health and overall medical outcomes.

2. Literature Review

This study [1] presents a multimedia-based patient monitoring system for smart healthcare, integrating speech and image data to assess user satisfaction. The system captures a patient's speech and facial expressions, transmits them to a cloud-based processing unit, and classifies satisfaction levels (satisfied, unsatisfied, indifferent) using a Support Vector Machine (SVM). Speech features are extracted using directional derivatives of a mel spectrogram, while facial features are obtained through Local Binary Patterns (LBP). The combination of both modalities enhances classification accuracy, reaching up to 93%. The system operates within a smart healthcare framework, where multimedia sensors in smart homes collect data for cloud processing. Experimental results demonstrate that multimodal inputs significantly improve recognition rates over unimodal approaches. This study [2] presents a secure and interpretable AI framework for epilepsy diagnosis using electroencephalogram (EEG) signals in smart healthcare systems. The proposed system, XAI-CAESDs, integrates three modules: feature engineering, seizure detection, and explainable decision-making. EEG signals are processed using the Dual-Tree Complex Wavelet Transform (DTCWT) to extract both linear and non-linear features, which are optimized using correlation coefficients and distance correlation techniques. A Stacking Ensemble Classifier (SEC), incorporating Random Forest (RF), Decision Tree (DT), and Extreme Gradient Boosting (XGB), is employed for classification. To enhance security, blockchain technology is integrated for encrypted EEG data storage. The system achieves high accuracy, outperforming existing models across three benchmark datasets (Bonn, UCI, and CHB-MIT), with validation accuracy reaching up to 99.6%. This paper [3] proposes a Federated Learning (FL)-based approach for collaborative and secure smart healthcare applications, integrating AI, edge computing, and blockchain for enhanced data privacy and real-time medical analysis. The framework processes patient data from IoT-based medical devices at the edge layer, reducing latency and computational costs while preserving privacy. A distributed AI training model is developed using Deep Reinforcement Learning (DRL), ensuring adaptive decision-making for various healthcare scenarios. To further secure patient data, the system employs blockchain-based encrypted storage and federated optimization techniques. The proposed architecture enhances medical diagnosis and treatment, achieving high accuracy in real-time healthcare applications. This paper [4] presents a blockchain-based healthcare platform designed for smart cities, ensuring transparency and privacy preservation in electronic health records (EHR) and insurance policies. The proposed system integrates Ethereum-based smart contracts and cryptographic techniques to enhance data security and user control. Patient data, including diagnostic reports, prescriptions, and insurance policies, are securely stored in an encrypted cloud while key information is maintained on the blockchain. The platform employs elliptic curve cryptography (ECC) for secure encryption and identity verification. By leveraging smart contracts, the system guarantees transparent insurance policy management, preventing fraud and unauthorized modifications. Experimental results demonstrate that the system achieves low latency and efficient transaction processing. Compared to traditional EHR solutions, this framework enhances security, trust, and data integrity in smart healthcare environments.

This paper [5] proposes a robust blockchain-enabled authentication and key management mechanism (SBAKM-HS) for smart healthcare applications utilizing the Internet of Medical Things (IoMT). The system ensures secure data transmission between smart healthcare devices, personal servers, and cloud servers, addressing potential cyber threats such as replay, man-in-the-middle (MiTM), and impersonation attacks. The SBAKM-HS integrates cryptographic techniques, including symmetric key encryption and elliptic curve cryptography (ECC), to authenticate entities and establish secure communication channels. A blockchain-based framework enhances data integrity and privacy by securely storing healthcare transactions in a distributed ledger, verified through a consensus mechanism. The security analysis, conducted via the Scyther automated validation tool, confirms resilience against various threats. The testbed implementation demonstrates real-time applicability, with low latency and high security. This paper [6] proposes a lightweight smart-contract-based transaction prioritization scheme (LSP) for smart healthcare, addressing the inefficiencies of traditional blockchain-based electronic medical record (EMR) systems. Unlike first-in, first-out (FIFO) transaction processing models, LSP introduces a deterministic prioritization method that ensures emergency healthcare transactions receive higher processing precedence without requiring higher transaction fees. The framework employs a stateless transaction model that categorizes EMR transactions based on service urgency and assigns priority scores using a standardized smart contract. The proposed scheme enables machine-to-machine communication, improving real-time emergency medical services (EMS) and resource allocation. Experimental evaluations conducted on a private Ethereum network demonstrate that LSP significantly reduces computation overhead compared to existing models, achieving faster transaction processing and lower latency. This paper [7] introduces a Federated Learning-based privacy protection framework leveraging Edge Intelligence to secure smart healthcare systems. The proposed approach, Federated Edge Aggregator (FEA), enhances privacy by integrating an intermediary edge layer between IoT devices and the central aggregator, preventing direct access to raw patient data. The framework employs a Convolutional Neural Network (CNN) model and applies differential privacy mechanisms using Gaussian noise perturbation to obscure sensitive information. Experimental evaluations on benchmark datasets, including MNIST, CIFAR-10, and COVID-19 chest X-rays, demonstrate improved model accuracy while preserving patient data privacy. The system achieves up to 90% accuracy and reduces computational overhead compared to conventional Federated Learning models.

This paper [8] reviews the role of Natural Language Processing (NLP) in smart healthcare, exploring its applications and technical foundations. NLP enables automated analysis and interpretation of medical text and speech, facilitating applications in clinical decision support, hospital management, personal care, public health, and drug development. Key NLP methodologies include rule-based, statistical, and deep learning approaches, with deep neural networks showing state-of-the-art performance in various healthcare tasks. The study highlights NLP's impact on COVID-19 research, mental health diagnostics, and healthcare automation, demonstrating improvements in efficiency and accuracy. Despite its advancements, NLP faces challenges related to interpretability, computational cost, and privacy concerns in healthcare applications. Future research directions include enhancing multimodal learning, developing end-to-end applications, and incorporating domain knowledge for improved precision. This paper [9] proposes a smart-contract-based access control framework for cloud-enabled smart healthcare systems, ensuring secure and decentralized management of electronic medical records (EMRs). The framework leverages blockchain technology to enhance data security, integrity, and transparency while mitigating the risks associated with centralized cloud storage. It introduces four smart contracts: validation, access authorization, misbehavior detection, and revocation. To optimize storage efficiency, encrypted EMRs are stored in the cloud, while their hash values are recorded on the blockchain. Cryptographic techniques such as elliptic curve cryptography (ECC) and the Edwards-curve digital signature algorithm (EdDSA) are employed to safeguard patient data. The system is implemented on a private Ethereum blockchain and demonstrates high efficiency in real-time healthcare scenarios. This paper [10] presents a blockchain-powered Parallel Healthcare System (PHS) based on the Artificial Systems + Computational Experiments + Parallel Execution (ACP) approach. The proposed PHS integrates artificial intelligence and blockchain technology to enhance diagnosis accuracy and treatment effectiveness. The framework employs artificial healthcare models to represent patient conditions, computational experiments for evaluating therapeutic regimens, and parallel execution to optimize real-time medical decision-making. A consortium blockchain links hospitals, patients, and healthcare agencies, enabling secure and auditable electronic health record (EHR) sharing. The prototype system, implemented for gout diagnosis and treatment, demonstrates improved efficiency and security in medical decision-making. The blockchain-powered PHS enhances interoperability, data integrity, and research collaboration in smart healthcare environments.

This paper [11] presents an obstetric imaging diagnostic platform leveraging cloud computing, big data analytics, and deep learning to enhance diagnostic accuracy and efficiency. The proposed system integrates a distributed file system with caching technology to improve medical image storage and retrieval performance. Contrast-enhanced ultrasound technology is employed to provide clearer imaging of the placenta, enabling precise assessment of its structure, size, and abnormalities. The system supports real-time obstetric image processing, reducing hardware costs and enhancing hospital efficiency by offloading computational tasks to the cloud. Experimental evaluations demonstrate that the platform significantly improves data processing speed and diagnostic accuracy. A hybrid storage architecture combining centralized and distributed systems ensures scalability and data security. This paper [12] presents a secure authentication protocol for the Telecare Medicine Information System (TMIS) and smart campuses, addressing vulnerabilities in existing authentication mechanisms. The proposed protocol enhances security against impersonation, replay, and desynchronization attacks while ensuring lightweight computational requirements suitable for RFID-based healthcare systems. The design incorporates hash functions and bitwise XOR operations to achieve efficient mutual authentication without relying on resource-intensive cryptographic operations such as elliptic curve cryptography (ECC). The system is formally verified using the Scyther tool, confirming its resilience against active and passive attacks. Performance evaluations demonstrate that the proposed protocol achieves superior authentication efficiency compared to existing schemes while maintaining robust security. This paper [13] presents a multi-sensor smart garment for continuous respiratory monitoring during physical activities. The wearable system integrates six piezoresistive sensing elements embedded in elastic bands positioned at the thorax and abdomen to capture respiratory rate (fR) in real-time. Bespoke signal processing algorithms are implemented to filter motion artifacts and improve measurement accuracy. The system was tested on ten male volunteers performing walking and running activities at controlled speeds (1.6–8.0 km/h). Experimental evaluations demonstrated high agreement between the smart garment and reference flowmeter measurements, with a mean absolute error (MAE) of <1.86 breaths per minute (bpm) and a mean percentage error of <2.83%.

This paper [14] presents the application of Narrowband Internet of Things (NB-IoT) in smart healthcare and the development of a robotic rehabilitation system for lower limb recovery. The proposed system integrates NB-IoT technology to enhance real-time patient data collection and remote monitoring while optimizing rehabilitation efficiency. The architecture consists of patient data acquisition hardware, an IoT cloud platform, and a hospital server, enabling seamless communication and medical data management. The lower limb exoskeleton rehabilitation robot utilizes deep learning-based predictive models, including XGBoost and LightGBM, for personalized rehabilitation strategies. Security measures are implemented to protect patient data transmission using multi-channel encryption. Experimental results demonstrate high accuracy in motion tracking, reduced packet loss rates, and improved rehabilitation outcomes. This paper [15] explores the role of wearable devices in precision medicine and health state monitoring, focusing on the continuous measurement of vital signs such as heart rate, respiration rate, blood pressure, temperature, physical activity, sweat composition, and emotional state. Wearable technologies enable real-time, high-resolution health data collection, supporting personalized medical decisions and improving patient outcomes. The study reviews various signal transduction methods, including electrocardiography (ECG), photoplethysmography (PPG), respiratory inductance plethysmography (RIP), and pulse transit time (PTT). The paper highlights challenges related to accuracy, motion artifacts, and data privacy while emphasizing the potential of AI-driven analytics in enhancing diagnostic precision.

3. Research Method

3.1 Positioning System Design

This study aims to develop an ocular cell localization method based on artificial intelligence (AI) technologies, leveraging various image processing and deep learning techniques to enhance image classification and cell localization accuracy. To achieve this goal, the study employs convolutional neural networks (CNNs), Canny edge detection, wavelet filters, the YOLO object detection model, and adaptive thresholding. Additionally, manual and semi-automated annotation techniques are integrated to construct a high-quality dataset. Since ocular cell images may be affected by noise, which impacts the accuracy of subsequent algorithms, this study adopts the following image preprocessing techniques to improve cell localization performance. The Canny algorithm, a widely used edge detection technique, is utilized to extract key features from images. By applying the Canny algorithm to identify the boundaries between cells and the background, this approach ensures effective separation and enhances the accuracy of subsequent cell localization. Furthermore, to reduce noise and improve image quality, this study employs four wavelet filters: Gaussian filter, blur filter, median filter, and bilateral filter. These filtering techniques effectively mitigate external interference, improve image processing precision, and enhance the reliability of cell localization.

Convolutional neural networks (CNNs) are implemented to automatically learn image features and perform image classification and cell localization. CNNs process images through an input layer, convolutional layers, pooling layers, and fully connected layers to predict cell locations. In addition, the YOLO (You Only Look Once) object detection model is employed as a high-efficiency cell localization technique, transforming object detection into a single neural network regression problem, thereby achieving high-speed computation and accurate cell boundary box prediction. To further improve localization performance, this study incorporates adaptive thresholding, which dynamically adjusts the threshold based on local brightness characteristics, enhancing cell contours and clarifying cell boundaries for subsequent analysis. After applying these techniques to process images, this study constructs a high-quality ocular cell dataset. The dataset annotation process includes manual and semi-automated labeling, where cell positions are manually annotated to create accurate ground-truth labels. The YOLO model and adaptive thresholding are then used for automated detection, followed by manual corrections to improve annotation efficiency. By integrating CNNs, the Canny algorithm, wavelet filters, the YOLO model, and adaptive thresholding, this study achieves an efficient ocular cell localization method. The combination of multi-layer image processing and deep learning techniques effectively enhances cell detection accuracy and ultimately facilitates the construction of a high-quality dataset, providing a reliable data foundation for future research.

3.2 Design Steps for AI-Based Ocular Cell Localization

The research design process encompasses image preprocessing, contrast adjustment, data labeling, model training, and testing to ensure optimal processing and localization of ocular cell images.

Step 1: Image Acquisition and Verification

First, raw medical images of ocular cells are collected and verified by professional ophthalmologists before being loaded into the compiler for further processing (Figure 1).

Step 2: Image Preprocessing

To reduce noise and enhance cell contour clarity, this study sequentially applied the following filtering techniques:

Blur filtering: Smooths the image and reduces high-frequency noise but may blur fine details.

Gaussian filtering: Reduces noise while preserving more image details, making it well-suited for ocular cell image processing.

Median filtering: Effectively removes salt-and-pepper noise with minimal impact on edge details.

Bilateral filtering: Smooths the image while preserving edge sharpness, enhancing the visibility of cell contours.

After comparative analysis, Gaussian filtering was selected as the primary preprocessing technique due to its ability to maintain cell contour clarity (Figure 2).

Step 3: Contrast Adjustment

To further enhance image contrast, various adaptive thresholding techniques were tested. The process involved:

Setting an initial threshold.

Adjusting the threshold to observe changes in cell contour visibility.

However, experimental results indicated that adaptive thresholding failed to fully retain distinguishable cell contours. Consequently, this method was discarded, and Gaussian-filtered images were used as the foundation for subsequent labeling.

Step 4: Data Labeling and Dataset Construction

In this stage, Roboflow was used for cell annotation, generating the training dataset.

Initially, Roboflow's automated annotation was applied to efficiently detect cell positions.

The annotations were manually reviewed and corrected to ensure accuracy and consistency.

Step 5: Model Training and Performance Evaluation

After annotation, the dataset was input into the YOLO object detection model to evaluate its cell localization capability.

Comparing different processing techniques, the detection accuracy results were:

Unprocessed images: 0% accuracy.

Automatically labeled data: ~20% accuracy.

Roboflow-assisted semi-automated labeling: 65% accuracy, the highest among the tested methods.

Step 6: Future Optimization and System Enhancement

The current study has achieved a 65% cell localization accuracy, but further improvements are possible. Future work will focus on:

Optimizing YOLO model parameters to improve localization precision.

Expanding the dataset to enhance model generalization.

Developing an intuitive user interface to facilitate ease of use for ophthalmologists.

Through these steps, this study successfully constructed an AI-based ocular cell localization system and demonstrated the applicability of image processing and deep learning techniques in medical image analysis.

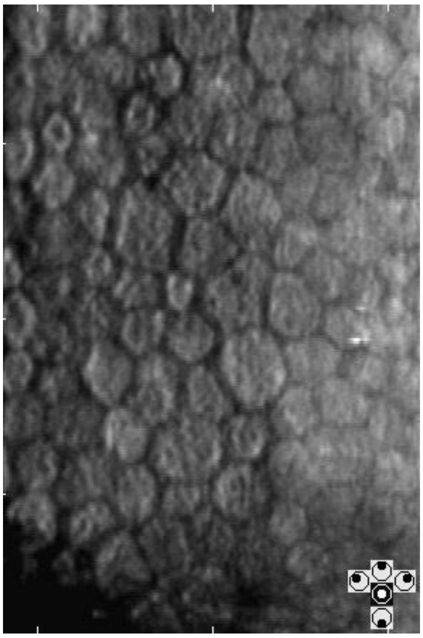

Fig 1. Professional Ophthalmologists

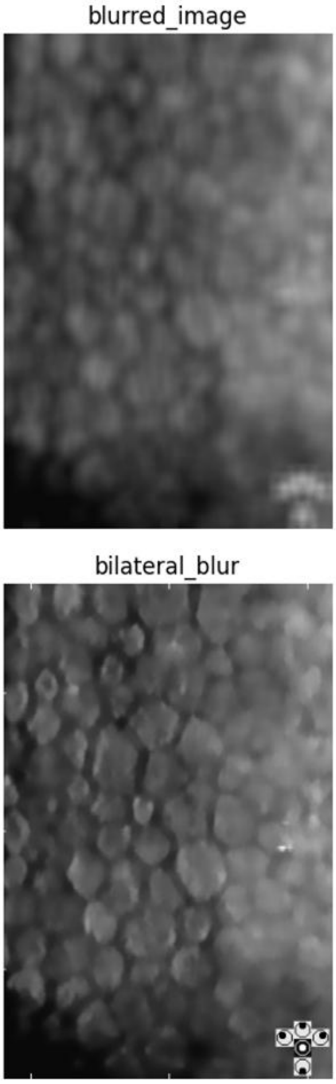

Fig 2. Maintain Cell Contour Clarity

4. Results and Discussion

This study enhances cell localization accuracy through a multi-stage processing technique and validates its effectiveness by comparing different methods. In the initial tests, the model was unable to correctly identify cells when no image preprocessing was applied, resulting in 0% accuracy, as shown in Figure 3. However, after introducing image processing techniques, including Gaussian filtering and an appropriate data labeling method, localization accuracy significantly improved. A comparison of different data labeling methods revealed that automatic labeling using Roboflow achieved an accuracy of approximately 20%, whereas semi-automated labeling, which incorporates manual refinement, increased accuracy to 65%. By improving labeling precision, the model was able to learn cell features more effectively, leading to enhanced prediction results.

To assess overall model performance, multiple images were tested, and accuracy, recall, and F1-score were calculated. The results indicated that when image preprocessing was optimized and labeled data were manually refined, the model achieved an F1-score of 0.72, as shown in Figure 4. This demonstrates the feasibility of the proposed method for ocular cell localization. Although the current study has achieved a 65% localization accuracy, there is still room for improvement. Future efforts will focus on optimizing YOLO model parameters to improve localization precision, expanding the dataset to enhance the model's generalization ability, and developing an intuitive user interface to facilitate ease of use for ophthalmologists. Through these steps, this study successfully constructed an AI-based ocular cell localization system and validated the application of image processing and deep learning techniques in medical image analysis.

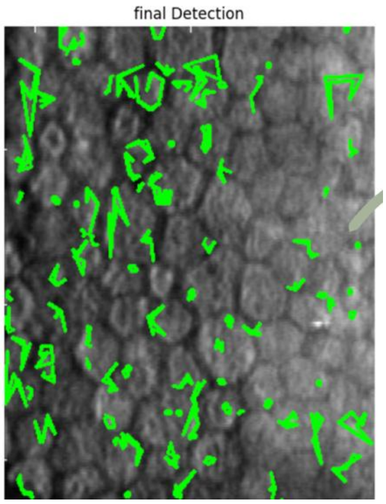

Fig 3. multi-stage processing technique and validates

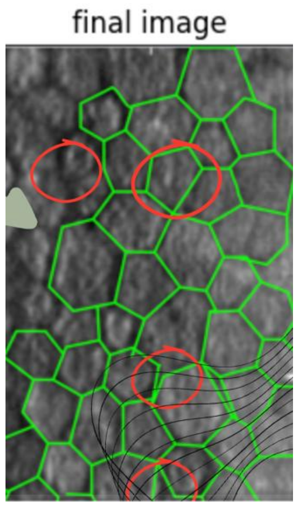

Fig 4. semi-automated labeling

5. Conclusions

This study successfully developed an AI-based ocular cell localization system, achieving a localization accuracy of 65%. While there is still room for improvement, these results demonstrate the feasibility and potential of integrating deep learning techniques into medical image analysis. In future research, we plan to further optimize system performance through several key approaches. First, we will adopt more advanced deep learning architectures to improve localization accuracy. Second, we aim to expand the dataset with a more diverse collection of medical images, enhancing the model's generalization ability to adapt to varying conditions in cell detection. Additionally, we intend to develop specialized models tailored for different ophthalmic diseases, increasing the practicality and clinical value of the system. We hope that this research will provide a powerful technological tool for ophthalmic diagnostics while inspiring further innovation and applications in medical AI. With continuous advancements in technology, we believe this system will achieve greater breakthroughs in accuracy, efficiency, and clinical application, ultimately benefiting both healthcare professionals and patients.

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