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Instantaneous Classification and Localization of Eye Diseases via Artificial Intelligence

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ABSTRACT

The primary causes of vision impairment worldwide include glaucoma, cataract, and retinal diseases. The increasing occurrence of these disorders requires a prompt and precise diagnosis. The proposed method aims to facilitate the diagnosis of glaucoma, retinal diseases, cataracts, and other conditions for individuals. Eye disorders are classified and localized through the utilization of convolutional neural networks and artificial neural networks. The proposed method aims to decrease the incidence of acquired blindness by allowing patients to access essential care for the specified diseases in the first stages. As well as assessing the prognosis of glaucoma and retinal diseases, the adopted methodology evaluates the efficacy and safety of cataract surgery in patients with age-related macular degeneration. This study exhibits the accuracy of algorithms by analyzing fundus images from eyes with glaucoma, healthy eyes, retina issues, and cataracts. Presently, the notion of classifying photographs according to their foundation and extracting characteristics is widely acknowledged, and it also serves an essential function in the final analysis.

Key words: Machine Learning, Imaging, Artificial Intelligence, Diagnosis**.**

INTRODUCTION

The advent of artificial intelligence (AI) has revolutionized medical diagnostics, and in the realm of ophthalmology, its impact is transformative. This study focuses on the real-time classification and localization of eye diseases, leveraging advanced AI algorithms. The intricate interplay of AI technologies enables swift and accurate identification of various ocular conditions, empowering healthcare professionals with timely insights for effective treatment. By amalgamating cutting-edge machine learning techniques, particularly Convolutional Neural Networks (CNNs), this research pioneers a paradigm shift in the field of ophthalmic diagnostics. The immediacy and precision offered by the AI-driven system provides an unprecedented advantage in early disease detection and localization. As we delve into the nuances of this groundbreaking approach, we unravel the potential to reshape the landscape of eye healthcare, offering rapid and reliable diagnoses that can significantly improve patient outcomes and contribute to the broader advancement of medical technology. The fast-paced developments in machine learning (ML) and artificial intelligence (AI) are leading to a significant shift in the healthcare sector (Lo et al., 2021) [1]. Identifying and pinpointing ocular disorders in real-time is a groundbreaking development among the numerous exciting applications of AI in the healthcare field (Harika et al., 2022) [20]. Undiagnosed or untreated eye conditions can lead to significant vision loss or complete loss of vision. This review explores the significant progress achieved in real-time early detection, classification, and localization of eye diseases by incorporating AI technologies. This review delves into the significant impact of artificial intelligence on revolutionizing the process of identifying and treating eye disorders for ophthalmologists and other medical professionals. We will explore the latest artificial intelligence (AI) algorithms, image processing techniques, and deep learning models developed for real-time analysis of medical images, such as fundus and retinal scans. Artificial intelligence offers the potential to facilitate rapid intervention and treatment through swift and precise detection and pinpointing of eye conditions, leading to enhanced patient results and reduced burden on healthcare systems. Ullah et.at (2023) and Shakil et al. (2013) finds the best scenario of a job shop production which will be helpful for reducing risk of this classifications when doing CNN method [30-35]. In their work, Jamil et al. (2024) intricately explore the optimization strategies applied to the domain of CNN (Convolutional Neural Network) imaging for material characterization. This study delves into the complexities associated with enhancing strategies in the context of mechanical material characterization, specifically addressing challenges related to variations in material properties. Their research contributes valuable insights into the field of CNN imaging, offering a nuanced understanding of how optimization techniques can be tailored to address challenges inherent to the intricate characterization processes associated with mechanical materials [36-42].

Additionally, this review will discuss the challenges and ethical issues surrounding the use of AI in ophthalmology, including data privacy issues, algorithm openness, the need for validation, and regulatory supervision (Lee et al., 2020) [2]. This study attempts to give a deeper understanding of the present status of artificial intelligence-based real-time categorization and localization of eye illnesses to determine the future of eye care and vision preservation (Rissati et al., 2020; Xu et al., 2021; Saini et al., 2023) [3,4,5]. It also aims to draw attention to this technology's possible benefits and drawbacks.

RELATED TO WORK

Some recent researchers work on disease diagnose with AI & Data analytics combination [44-49] and according to (Yow et al., 2017) [6], AVIGA is an automated method for tracking gaze that can detect vision impairment developed by QTanalytics India in 2023. Impulse Stimuli Response (ISR) and Pursuit Stimuli Response (PSR) tests are two kinds of evaluations that were implemented in the AVIGA system. A support vector regression (SVR)-based approach is employed to classify the degree of vision impairment according to the assessment outcomes. In terms of diagnosing visual impairments, the results show that the AVIGA method is superior to microperimetry and correlates strongly with the visual acuity test (VA). The proposed computer vision model can rapidly identify several illnesses and has the potential to automate the detection of eye disorders on a wide scale (Nair et al., 2021) [7]. The suggested approach, based on the hamming losses presented, may have limited illness detection capabilities. However, this can still significantly benefit ophthalmologists working in these camps by reducing their workload.

Based on the findings of (Kazi et al., 2018) [8], the authors proposed a technique for determining eye diseases that involves the removal of blood vessels from the retina. To identify the existence of an exudate and categorize it as either diabetic retinopathy, glaucoma, or cataract, deep convolutional neural networks will be developed and then put into use. The establishment of a system that can determine the possibility of illnesses occurring in addition to determining whether they are present. The idea put forward would enable patients to obtain timely care for the specified illnesses, hence decreasing the incidence of blindness caused by these conditions (Karahan & Akgul, 2016) [9]. We utilize Support Vector Machine, Gradient Boosting, Random Forest, and Logistic Regression for detection. Eye disorders may be recognized 90% of the time. Rahman et al. (2023) and Ibtisum et al. (2023) analysis of big data tools which is very helpful for our research specifically when we consider confusion matrix for testing & training dataset [22-28]. Studies in this research found that by normalizing facial images, they could make blink detection more accurate and less noisy (Kuwahara et al., 2021) [10]. Using EARM, they found that the proposed method achieved better blink detection accuracy than any of the test results. To uncover hidden traits for this investigation, fundus photos of both healthy and sick individuals are captured in well-lit settings (Shainia et al., 2022) [11]. After capturing the fundus images, they are enhanced using power transform, grayscale conversion, and resizing methods. For the final step, we will construct a deep CNN with one hidden layer, 16 input neurons, and either Evo healthy or Evo damaged output neurons. 91% of identifications are accurate. This project aims to develop a system to help ophthalmologists identify, diagnose, and treat eye strabismus without requiring spectacles, painful laser treatments, or medications (Daher & Rainmal, 2021) [12]. Our system has demonstrated the ability to distinguish between patients with normal and abnormal conditions, determining deviation percentages and levels of abnormality, assessing ocular vibration levels, and addressing a range of eye ailments. The proposed technique explores the use of machine learning to differentiate diabetic eye disease from other eye conditions by analyzing thermography images of the eyes (Selvathi & Suganya, 2019) [13]. The text discusses the impact of thermal variation on abnormalities in eye structure as a diagnostic imaging tool that aids ophthalmologists in making clinical diagnoses. In terms of eye illness classification, this study found that a combination of Support Vector Machine and K-Nearest Neighbor was more accurate than SVM alone (Wardani & Sihombing, 2020) [14]. The combined accuracy of the SVM plus KNN technique is 94.67%.

METHODOLOGY

We're presenting a methodology for categorizing and pinpointing eye conditions, utilizing fundus images of the retina as input and artificial intelligence for data analysis and result generation. The proposed method follows a layered structure like a convolutional neural network (Priyadharshini & Dolly, 2023) [15,43]. In this scenario, each layer has specific functions for supervised training, with the dense network handling the training process (Tendle et al., 2022; Liang et al., 2021) [16].

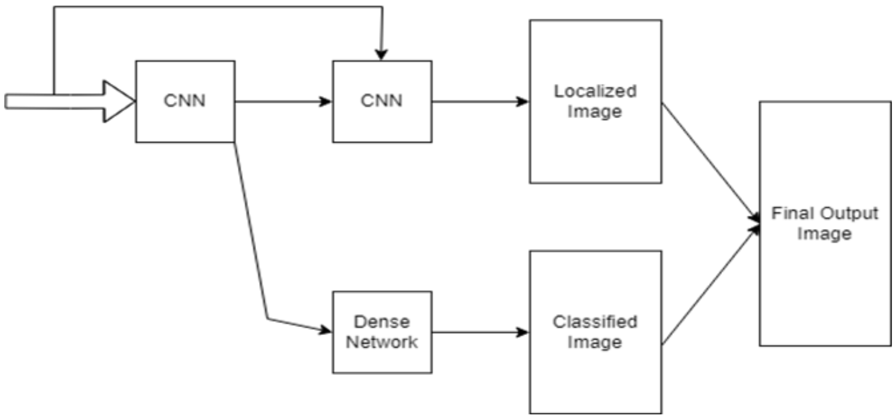

Figure 1: Block Diagram for CNN and Dense Network-Based Classification and Localization of Eye Diseases

The diagram in Figure 1 illustrates the functioning of the model that has been put into practice. One CNN block is utilized for feature extraction, while the other is employed for generating masks (Yuningsih et al., 2022) [17]. Following feature extraction, the image proceeds to localization. Utilizing a dense network, the eye data set can be classified into normal or abnormal eye conditions. When the image is localized, it indicates a problem in the retina and is classified as abnormal. If there is no specific localization in the eye, it is considered normal. This approach will make the proposed concept successful.

3.1 Artificial Neural Network

The identification of eye diseases has seen remarkable advancements through the analysis of medical photographs, particularly optical coherence tomography (OCT) and retinal scans. Milanovic et al. (2021) and Malik & Kamra (2021) have demonstrated the efficacy of Artificial Neural Networks (ANNs) in this realm [18,19]. Leveraging a substantial dataset comprising annotated images, these ANNs are trained to discern a variety of eye conditions, with labels indicating their presence or absence. During the testing phase, the ANN utilizes this training to predict the health conditions based on new images. Convolutional Neural Networks (CNNs) have proven instrumental in diagnosing numerous eye diseases, including diabetic retinopathy, age-related macular degeneration, and glaucoma. The application of CNNs significantly enhances the precision of predictions. In this context, Mustaquim (2014) provides valuable insights into the mathematical sensing of data used for land surface temperature. This mathematical approach, particularly the use of gradCAM in our project for detection purposes, is instrumental and aligns seamlessly with our ongoing research [29]. This amalgamation of cutting-edge technologies, encompassing ANNs, CNNs, and mathematical sensing techniques, marks a transformative approach in the realm of eye disease identification. The utilization of annotated datasets for training, coupled with sophisticated neural network architectures, showcases the potential for accurate and timely diagnoses. Furthermore, Mustaquim's work highlights the applicability of mathematical sensing data in our project, elucidating the intricate dynamics of land surface temperature for enhanced detection capabilities. Overall, the convergence of artificial intelligence and mathematical methodologies holds promise for revolutionizing the landscape of medical diagnostics, particularly in the domain of eye diseases.

3.2 Convolutional Neural Network

Convolutional Neural Networks (CNNs), which belong to the deep learning neural network subclass, exhibit exceptional proficiency in image classification tasks, including the identification of various retinal conditions. CNN can be trained for recognizing eye disorders by employing a large dataset of medical images, including optical coherence tomography (OCT) images and retinal scans. CNN trains itself to recognize patterns in images that may represent various eye conditions. Throughout the training process, CNN is presented with an extensive range of visuals depicting both healthy and diseased eyes, accompanied by labels that specify the existence or non-existence of eye disorders. CNN progressively improves its ability to differentiate between various types of eye diseases by analyzing the patterns in the photographs. After being trained, CNN can be utilized to predict outcomes for completely fresh and unseen images. A prediction of potential eye diseases is generated by CNN through analysis of the image. The prediction is developed using the patterns identified in the training data. Consistently identifying a range of ocular disorders, including diabetic retinopathy, age-related macular degeneration, and glaucoma, CNNs have demonstrated favorable results due to their high rates of precision. In the 2023 research conducted by Syed et al., a thorough account is presented detailing their strategy for the classification of brain tumors through transfer learning, emphasizing its relevance in healthcare applications. The study adopts an approach grounded in Deep Learning, a potent methodology that encompasses multi-stage neural network analysis. This research proves to be an invaluable resource for students aspiring to delve into medical imaging, offering significant insights into the intricate process of utilizing transfer learning for the classification of brain tumors. Our research methodology is solely based on the concept that comes from this paper and it is an excellent paper for tumor classification analysis specifically for convoluted neural network [21].

EXPERIMENTAL SETUP

The system is meticulously crafted using the Python programming language, and a versatile codebase is implemented for seamless integration with the system's utilities. Image processing within the system is executed using a TensorFlow (FP16) processor configuration, ensuring efficient handling of complex tasks. The system demonstrates compatibility with video cards boasting substantial capacities, including the 12GB NVIDIA RTX A6000, GeForce RTX 3080, and AMD Radeon RX580. This diverse card support enhances the system's adaptability to different hardware configurations. To facilitate the acquisition of essential data for the system, Kaggle serves as a reliable platform. Kaggle, a well-established online community for data scientists and machine learning practitioners, provides accessible resources for obtaining the necessary datasets, streamlining the data collection process. The utilization of powerful hardware configurations coupled with Python's flexibility and Kaggle's data resources collectively positions the system as a robust and versatile solution for image processing tasks. This amalgamation of technological components reflects a thoughtful approach to system design, aiming to cater to diverse user needs and optimize performance in image-related processes.

F—Measure

Assigning an input image to one of numerous specified categories or classes is a common objective of 2D image classification tasks, for which the F-Measure is a prevalent evaluation metric. As presented in Table 1, the F-Measure summarizes the performance of a classification model by combining the two critical metrics of recall and precision.

The F-Measure can be computed as follows for a variety of eye diseases:

$$\text{F-measure} = 2 \times \frac{(\text{Recall} \times \text{Precision})}{(\text{Recall} + \text{Precision})}$$

$$\text{F-measure for cataract} = 2 \times \frac{\text{Recall for cataract} * \text{Precision for cataract})}{(\text{Recall for cataract} + \text{Precision for cataract})}$$

$= 2 * (0.8 * 0.85) / (0.8 + 0.85)$

$= 0.8242$

Table 1: Calculation of F-Measure for diabetic retinopathy, cataract, and glaucoma

Calculation of F- Measure				
Eye Diseases	**Disease Type Code**	**Precision**	**Recall**	**F-Score**
Diabetic Retinopathy	1	0.81	0.82	0.8932
Cataract	2	0.72	0.79	0.7725
Glaucoma	3	0.7	0.89	0.7624

RESULTS

As an example, if the dataset comprises 1000 photographs and the model effectively categorizes 900 of them, the accuracy would be calculated as follows:

Accuracy = $\frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100\%$

= (900 / 1000) × 100%

= 90%

The rate at which a system can complete a specific quantity of work in a specified period is referred to as its throughput.

Processing time per image = $\frac{\text{Total processing time}}{\text{Number of images processed}}$

Processing time per image = 10 minutes / 80 images

= 0.125 minutes per image.

Throughput = $\frac{1}{\text{Processing time per image}}$

= 1 / 0.125 minutes per image

= 8 images per minute

In this case, the system improves both accuracy and throughput. A comparison between the outcomes obtained by prior authors and the anticipated improvements in accuracy and throughput is presented in Table 2.

Table 2: Results obtained for accuracy and throughput utilizing different AI algorithms.

Model of Artificial Intelligence Using GN				
Input Data Format	Processing Method	Extraction of Features	Accuracy	Throughput
Scanned Fundus Images	Feature Extraction &CNN	Blood vessel	92 %	8 images/s

Enhancing accuracy and throughput can be achieved by adjusting picture processing time through the implementation of quicker image processing techniques. An artificial neural network is suggested for compatibility with medical imaging. The following results are intended to be achieved. The planned work is based on empirical analysis, and experimental setups will be built as outlined in Table 3.

Table 3: A comparison between the outcomes anticipated in terms of accuracy and throughput and the results obtained by previous authors.

Name of Model	**Other authors' Accuracy**	**Proposed Accuracy**	**Other authors' Throughput**	**Proposed Throughput**
CNN	89 %	93 appx	8 images/s	8 images/s

CONCLUSION

The use of AI systems for the diagnosis and localization of eye problems such as glaucoma, diabetic retinopathy, age-related macular degeneration, and others has shown promising results. To accurately extract important details from images and generate predictions, these models utilize Convolutional Neural Networks (CNNs) with (Rectified Linear Unit) ReLU activation functions. Several factors can influence the performance of these models, including the task at hand, the quality and quantity of the dataset, and the design of the model. In general, however, the results have been promising, as multiple studies have documented remarkable levels of accuracy in both localization and classification for an extensive range of eye diseases. By diagnosing patients rapidly and precisely, these models eliminate the necessity for invasive procedures and improve patient outcomes; thus, they have the capacity to revolutionize the identification and treatment of retinal disorders. Further research and development in the domain of deep learning could yield more accurate and efficient models, which would be beneficial for healthcare professionals and patients alike. Positive classification and localization results for a range of ocular disorders have been achieved with the ReLU activation function and convolutional layers.

Future Work:

Refining the deep learning models used for disease classification and localization is essential, incorporating advanced architectures such as attention mechanisms and transformer-based models to improve accuracy and robustness. Additionally, exploring multi-modal approaches by integrating diverse imaging techniques like OCT, fundus photography, and angiography could provide a more comprehensive understanding of ocular pathologies. Investigating the interpretability of the AI models is crucial for gaining clinicians' trust, thus developing methods to generate interpretable explanations for the model's predictions is a priority. Collaborations with healthcare professionals and institutions should be intensified to ensure the seamless integration of the AI system into real-world clinical workflows. Furthermore, continuous updates and retraining of the AI model with new datasets and emerging eye disease data will be essential to adapt to evolving diagnostic challenges. Privacy and ethical considerations should be addressed by implementing secure and compliant data-sharing frameworks. Finally, the development of user-friendly interfaces and mobile applications for real-time deployment in various healthcare settings could facilitate widespread adoption and usage, thereby maximizing the impact of AI in eye disease diagnosis and management.

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