Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume XX Issue XX
202X

Review Article
https://doi.org/10.56979/601/2023

Deep Learning-Based Ophthalmic Disease Detection: A Systematic Review

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Received: October 12, 2023 **Accepted:** November 21, 2023 **Published:** December 05, 2023

Abstract: It is alarming that millions of individuals worldwide are affected by eye abnormalities that can potentially lead to vision loss if not detected and treated promptly. However, the process of manually identifying these diseases is both time-consuming and monotonous, lacking consistency. To address this issue researchers have turned their attention to automating ocular disease detection through the use of Deep Convolutional Neural Networks (DCNNs) and despite their potential, these models face challenges due to the intricate nature of eye lesions. In this study, we aim to assess the most prevalent ocular pathologies while providing an overview of these major diseases with their detection of common imaging methods. Moreover, we critically evaluate current deep-learning research in terms of its ability to detect and grade conditions such as glaucoma, diabetic retinopathy, Age-Related Macular Degeneration, and other ocular diseases. Our research concludes that CNN powered by deep learning will become increasingly essential as a supporting technology. Further efforts should focus on exploring the potential impact of utilizing ensemble CNN architectures in tasks involving multiple classes and labels. Additionally, the development of interpretable models is crucial to establish trust among clinicians and patients, and in this regard technology is effectively assisting the doctor, and deep learning technology is one example.

Keywords: Ophthalmic Disease; Deep Learning; CNN; Diabetic Retinopathy; Glaucoma; Cataract.

1. Introduction

Rooted in Greek terminology the word "Ophthalmo-" translates to "eye " while "-logia" signifies "study of Its integration into the English language dates back several centuries but finds its origins deeply embedded within history. A medical practitioner specializing in treating various eye disorders is designated an ophthalmologist. Ophthalmologists possess the expertise necessary to offer comprehensive vision care services encompassing eye examinations, prescription eyewear like glasses or contact lenses as well as management of diverse visual ailments ranging from common refractive abnormalities to intricate conditions such as cataracts, glaucoma, and other visual diseases. As the global population continues to expand ceaselessly, one observes an inevitable surge in eye conditions and visual impairments, a trend expected to intensify further in the coming years. According to World Health Organization (WHO) statistics more than 2.2 billion people currently struggle with either low or impaired vision, meanwhile at least 1 billion individuals grappling with impaired vision have the potential for restoration [1]. Globally. It is estimated that around 285 million people will face vision difficulties in the future comprising 246 million individuals with diminished visual capabilities and 39 million others categorized as blind [2]. Accessing eye care treatment remains a challenge, particularly in middle-income countries due primarily to exorbitant costs primarily associated with labor-intensive efforts. The findings gleaned from the 2013 Urban Health Survey reveal that inhabitants of slum areas often suffer from substandard physical health mirrored by mental health complexities. Consequently, numerous ocular disorders elude detection or manifest at an advanced stage ultimately leading to permanent blindness and a compromised quality of life for those affected by these circumstances. Early identification coupled with timely evaluation is paramount to effectively address eye ailments and prevent avoidable blindness.

In recent years there has been a rising focus on the systematic identification and evaluation of various health issues, particularly vision problems. One area of great interest has been the use of algorithms based on deep learning. These methods, known as Deep Learning (DL) oriented methods have shown impressive performance in a range of activities, such as sentiment assessment, object identification, stratification of medical photos, and disease recognition [3]. Utilizing deep learning for the automatic detection of eye illnesses can revolutionize ophthalmology by significantly improving monitoring and treatment processes in terms of efficacy, speed, and efficiency. Despite several studies yielding positive outcomes only a small percentage have been successful in fully diagnosing multiple eye illnesses. However, there are numerous advantages to be gained from automated vision impairment diagnosis. Firstly, automating the detection and evaluation process can alleviate the workload of eye specialists by allowing them to focus on more complex cases and reducing the risk of human error. Secondly, deep learning methods are capable of identifying subtle changes in healthcare images that may be missed by human observers. This can greatly enhance reliability and precision when it comes to screenings and diagnoses. Lastly, by enabling testing and diagnosis to be conducted virtually or in regions with limited access to optometrists it can greatly improve accessibility to ophthalmic care facilities [4].

1.1 Technical Deep Learning Features

When analyzing and making decisions using computational approaches, particularly in the context of medical images, there are several commonly used phrases. One such phrase is computer-assisted treatment, which refers to techniques that utilize specific tools and filters for image processing to uncover disease-related clinical features [5] whether the training process involves supervision or not. Machine learning (ML) is often used to describe any pattern classification method that learns about distinguishing characteristics within patterns [6] and Deep learning (DL) encompasses ML techniques and primarily relies on convolutional neural networks (CNNs), which use various picture processing techniques to identify visual elements indicative of unhealthy conditions based on the training data [7]. The use of CNNs and image processing filters are essential in DLs' pattern categorization methods. DL can be considered an effective approach for identifying suitable image processing tools or filters for evaluating disease biomarkers. In a broader sense, artificial intelligence (AI) refers to machine learning-based systems that can autonomously discover new patterns without external assistance usually from humans. The existence of a true AI system is still a subject of debate in this AI Deep Learning field.

When CNNs first emerged for practical applications, one major challenge was their limited processing capability. However, advancements in GPU technology changed the game for deeper CNNs or deep learners. These GPUs now outperform CPUs significantly when it comes to computing power. This breakthrough has enabled much faster and more efficient execution of CNN algorithms with deeper levels. As a result of this development, the industry has widely embraced deep neural network-based DL approaches that utilize structures like AlexNet [8], GoogleNet [9], VGG [10] and so far. These DL architectures offer tremendous breadth and detail that yield exceptional results in tasks ranging from image classification to object recognition and semantic segmentation. The capabilities showcased by these DL architectures span various fields with impressive outcomes. Moreover, DL solutions exhibit promise in areas such as creating algorithmic suggestions similar to Netflix's method for collecting diverse image assortments. Notably, there is an ongoing effort to evaluate these systems' performance in clinical domains, with a particular focus on biomedical image processing. The aim of these initiatives is to leverage DL's capabilities to enhance medical imaging activities including diagnosis, disease detection, and medical image interpretation. Ultimately, these endeavors are expected to contribute to better healthcare outcomes.

There are two main categories of DL solutions for biological-image analysis:

1. Methods for classifying photos: In these techniques, the DL network is fed images and their accompanying conditions of use, such as assessments, labels, or stages. Based on these related conditions, the network trains to categorize the photos. The focus of this category, often known as picture classification, is on determining if certain disorders or diseases are present or absent.
2. Semantic segmentation techniques: In this class, pictures and manually drawn ground-truth masks are sent to the DL network. The precise regions or borders connected to the pathological circumstances associated with the disease are highlighted in these masks, resulting in images. By precisely locating and dividing each region of interest inside the images, the algorithm learns to carry out semantic segmentation.

This paper's major goal is to provide a comprehensive and well-organized summary of the corpus of work that is currently accessible on the application of conventional deep learning techniques. It provides insightful information about the benefits and restrictions of using deep learning methods to diagnose conditions involving eye diseases. Readers can have a thorough grasp of the advantages and disadvantages of using deep learning techniques in the discipline of ophthalmology, particularly with regard to ocular disorders, by studying this research.

2. Related Work

Extensive research [11-13] has been conducted to develop advanced medical technologies capable of automating eye disease examinations. However,these technologies are limited by rigid standards and struggle to adapt to new situations leading to subpar outcomes. To address this issue deep learning techniques that utilize training data to expedite learning have gained popularity. As a result, machine-based investigations in various medical specialties, especially ophthalmology, have increased. In this context, a concise overview of relevant studies will be presented.

With increasing age and obesity rates among individuals,the number of cases of DR is rising dramatically resulting in visual loss being one of its main consequences [14,15]. Multiple investigations are underway to create software applications that can enhance both the detection and administration aspects associated with this condition. Recent studies have demonstrated that artificial intelligence methods, such as SVM, RBF, multiple-layer perceptual classes, and DL-based approaches [16], are capable of identifying specific features associated with DR by analyzing retinal pictures. The diagnostic outcomes yielded by these AI tools exhibit comparable efficacy when compared to optometrists examining these identical pictures. Moreover, studies such as the ones carried out by[17-20] have employed vast datasets comprising both normal and DR images. These studies have yielded highly commendable results in relation to the accuracy of DR diagnosis (with sensitivity values ranging from 92.5% to 92.7%, specificity values ranging from 86.7% to 96.1%, accuracy values ranging from 80.8% to 94.1%, and AUC values of 99.2%) by identifying specific characteristics and making distinctions between affected and unaffected images these software programs can effectively evaluate and categorize different stages of DR. Additional research is needed to fully assess the significance of deep learning in this selection process.

Age-related macular degeneration (AMD) and diabetic macular edema (DME) are two retinal conditions that can be identified monitored and treated using OCT scanning. Deep learning algorithms have garnered considerable attention as a means to intelligently analyze OCT scans for diagnostic purposes. Various methods have been developed to recognize typical OCT images and specific reference points have been identified [3]. The spectral domain OCT reveals 10 skeletal layers that are crucial for diagnosis with levels 4 to 10 being identifiable by current techniques. However,multiple studies have demonstrated significant variations in the identification of certain landmarks. It is imperative to urgently establish a reliable method by incorporating these techniques into a tele retinal monitoring pipeline automated OCT interpretation can be integrated into clinical practice. Automated OCT analysis has displayed promising results in detecting exuding AMD and DME[21, 22]. In a previous study conducted by Matsuba, S., et al. referable AMD was detected with a sensitivity of 100% specificity of 97.31%, and an AUC of 99.67% [23].

When the outcome on the AUC curve is above 0.7 It indicates remarkable results conversely. When the outcome is below 0.5 It signifies subpar categorization. Therefore, deep learning holds the potential to accurately identify AMD in its early stages. OCT has demonstrated exceptional accuracy in detecting small amounts of fluid and determining the need to initiate treatment in neovascular AMD. In terms of identifying exudative AMD, TY Heo et al.[10] reported a precision score greater than 90%. The utilization of automated optical coherence tomography (OCT) scan analysis has shown promise in detecting various ophthalmic conditions such as diabetes-related retinopathy, central serous chorioretinopathy, polypoidal choroidal vasculopathy, and macular holes. For doctors, OCT analysis algorithms can serve as a valuable tool by helping prioritize cases and selecting appropriate medical treatments.

3. Materials and Methods

3.1 Resources of Search

We conducted a study using credible search engines, including IEEE Xplore, MDPI, Springer, Science Direct, and Google Scholar, and other to acquire information on deep learning approaches for the diagnosis of ophthalmological illnesses. The foundational study resources that weren't immediately related to our major issue were initially disregarded. Then, using established standards of assessment, we conducted a thorough analysis of a few chosen academic papers and conference documents.

3.2 Selection Criteria

Research articles and proceedings were first chosen according to a set of standards, including the paper's language, the year it was published, and the topic's applicability to the chosen discipline. The only academic writing employed in this study was that which was authored in English. In our review piece, we primarily looked at research that was published between 2019 to 2023. The chosen articles have to be pertinent to the search terms included in the ordered framework.

3.3 Procedure of Evaluation and Selection

Based on the specified search criteria, we were able to locate a total of 110 research articles and conference reports from this pool of papers. We carefully handpicked 75 publications with titles that we deemed relevant to our investigation out of these selected publications. A further 64 research articles were chosen for examination. We then proceeded to evaluate the significance of the abstracts of these chosen research articles before conducting more detailed studies on them. After thoroughly reviewing the quality of these papers we ultimately settled on 39 research articles for our final assessment when considering the final selection as indicated in Table 1.

Table 1. Search outcomes

No.	Source	Early Search	Selection based on time	Selection based on Abstract	Final Paper for study
1	GOOGLE SCHOLAR	48	36	30	21
2	SCIENCE DIRECT	22	13	11	3
3	IEEE	17	11	9	7
4	SPRINGER	13	7	7	4
5	MDPI	10	8	7	4
	TOTAL	110	75	64	39

We addressed many quality control questions after thoroughly analyzing the full texts of the chosen research publications to assess the caliber of the studies in this comprehensive review, we put the following questions forward.

- Was every aspect of the topic under review adequately covered by the selected research?
- Can we justify the quality of the chosen article?
- Does the chosen study effectively address the problems identified by the study?

The thorough explanation of deep learning methods for eye disease screening was the main component assessed in the first quality assessment question. Only research that is extremely pertinent to our field of study was chosen. To be considered for inclusion, these articles are required to clearly address the earlier specified research issues. Research articles that contained extraneous information or did not effectively address research or quality control issues were disqualified from consideration.

4. Deep Learning Method

The significant impact that the CNN technique has on picture categorization and we made the decision to utilize it for our review study. CNNs are exceptionally adept at automatically uncovering and extracting relevant features from imagesenabling accurate categorization due to this capability. They have revolutionized computer vision tasks and are now extensively employed across various applications. The main objective of our review is to provide insights into the advancements, applications, and challenges associated with CNNs in image categorization.

4.1 The method employed in the detection of ophthalmology disease using CNN

A specific type of neural network that has been developed for studying images is called a convolutional neural network (CNN). It consists of interconnected layers that utilize image data to analyze information. The visual data, which can be represented as tensors is inputted into the first layer known as the input layer. Convolutional layers apply filters to the input-extracting features such as edges and textures. Activation functions are introduced to capture complex interactions and introduce non-linearities. The extracted features are down-sampled by pooling layers in order to make predictions fully connected layers combine these features. The output layer delivers the final results based on the specific goal whether it is classification or estimation. When training a CNN with labeled data backpropagation is utilized to update inputs and minimize a loss function during inference. The trained CNN examines new data and provides predictions or classifications accordingly. CNNs have demonstrated exceptional performance in image processing tasks and have achieved significant success in various applications within ophthalmology. They have greatly assisted in detecting and treating eye conditions.

By categorizing extracted featuresCNNs can effectively diagnose eye disorders by training on a labeled dataset consisting of input photos that are classified as indicative of different eye illnesses or as healthy. The level of detail in the input images impacts the design of a CNN particularly determining the number of hidden layers required. The input dataset establishes connections between the hidden and input layers within the network’s architecture. Both supervised and unsupervised learning approaches can be employed to handle the dataset appropriately. Increasing attention has been paid to Convolutional Neural Networks (CNNs) due to their remarkable capabilities in image analysis research. The distinctive architecture, consisting of interconnected layers processing pictorial information provides a powerful tool for evaluating diverse images. Based on the nature of image analysis CNNs have illustratively shown their effectiveness in numerous domains, including security surveillance,autonomous driving systems, medical image processing, and many others.

Over time, various CNN models have been created, each with unique architectural alterations and advancements. Here are a few well-known CNN models:

4.1.1 AlexNet

AlexNet has been trained using a substantial dataset of labeled ophthalmic images specifically focusing on the identification of ophthalmology diseases by analyzing the photos, the network is able to extract relevant information such as textures, forms, and anomalies that are characteristic of different diseases. These photos are then classified into various disease groups based on these extracted attributes due to its unique architecture. AlexNet is highly effective in detecting and diagnosing diseases by capturing intricate patterns and variations in ophthalmic images. Once trained the AlexNet model can be applied to analyze new and unexplored ophthalmic pictures providing predictions and categorizations based on the identified features. The successful application of deep learning in this field serves as evidence for its efficacy in diagnosing eye diseases.

4.1.2 VGGNet

The use of VGGNet, a deep CNN architecture can also contribute to the detection of ophthalmological illnesses. One notable feature of VGGNet is its straightforward and standardized design with multiple layers comprising small filters. Training this model on a labeled dataset of ocular images allows it to acquire expertise in identifying relevant elements that serve as indicators for various diseases. The acquired knowledge is then utilized in the classification process where these attributes play a significant role. The advantage offered by VGGNets' deep architecture lies in its ability to accurately recognize diseases by detecting intricate details and subtle changes present in ophthalmic images. By analyzing previously unseen ophthalmic images using this trained VGGNet model, predictions or classifications based on learned features can be established, thereby facilitating identification and care for individuals with ophthalmological illnesses.

4.1.3 GoogLeNet

When it comes to diagnosing ophthalmological conditions, GoogleNet (also known as Inception) stands out as a highly effective and reliable deep CNN solution. What sets it apart is its clever employment of inception modules, which efficiently capture spatial information by utilizing different filter widths at each layer. By training GoogleNet on a carefully labeled dataset consisting of diverse ocular images related to ophthalmology illness identification, the network gains an exceptional ability to extract enlightening properties closely associated with specific diseases. This ability proves invaluable when it comes to making accurate diagnoses since GoogleNet's inception modules possess an impressive knack for recording intricate textures and structures present in ophthalmic pictures. The real power lies in leveraging this trained GoogLeNet model for analyzing novel ocular images through this process, meaningful forecasts or categorizations based on discovered features become achievable goals that significantly aid in early detection and treatment efforts targeting ophthalmological illnesses.

4.1.4 ResNet

Early diagnosis of ophthalmological illnesses can be greatly facilitated by the use of ResNet, a deep convolutional neural network (CNN) architecture. ResNet addresses the challenge of vanishing gradients by employing shortcuts or residual connections. These connections enable the network to capture residual mappings thereby simplifying the training of deep networks. In the field of ophthalmology, ResNet is trained on a labeled dataset comprising ocular images with the aim of diagnosing diseases by leveraging the power of residual connections, the network learns to extract disease-specific features from the images enabling more precise disease diagnosis even in cases where complex network structures are involved. As a result. ResNet enhances our ability to detect and care for ophthalmological illnesses by accurately capturing small details and comprehending intricate correlations within ophthalmic images.

4.1.5 DenseNet

A highly beneficial tool in identifying ocular conditions is DenseNet - an advanced convolutional neural network design that boasts sophistication in this particular field. Notably, this design incorporates densely linked blocks, ensuring each layer obtains direct input from all levels above it by restricting connectivity, feature reuse is encouraged, effective parameter sharing becomes feasible, and the challenge of gradient disappearance is mitigated. Through its reliance on a categorized collection of ocular images for learning purposes in diagnosing ophthalmology diseases, DenseNet harnesses dense connections to acquire the ability to identify specific disease features present within photos. As a result, the network proves adept at recognizing complex variations and patterns found in ocular pictures - ultimately enabling precise illness detection. Given its expansive connectivity capabilities, DenseNet emerges as an invaluable asset for ophthalmic diagnostics and therapy by promoting vigorous yet efficient disease detection methods.

4.1.6 MobileNet

When it comes to detecting ocular problems, the popular DCNN architecture known as MobileNet comes into play. This particular architecture is purposely designed to cater to hardware with limited resources - think embedded or mobile systems. What sets MobileNet apart in terms of computational efficiency are its depth-wise detachable convolutions that can reduce factors whilst maintaining accuracy. For teaching purposes, MobileNet relies on a categorized dataset of ocular images against the backdrop of ophthalmology illness identification. Thanks to its utilization of depth-wise separable convolutions, this network effectively learns how to extract disorder-specific details from these images. Consequently, diseases can be accurately and quickly identified, especially on devices with constrained computing capabilities. The low-cost architecture and effective calculations offered by MobileNet greatly benefit real-time ophthalmic disease detection apps since they enable swift diagnosis and timely therapy options.

4.1.7 Efficient Net

EfficientNet stands out as an advanced deep convolutional neural network architecture that excels at identifying ophthalmic conditions with remarkable accuracy. Its design prioritizes maximizing performance through precise network scaling techniques within the architecture of EfficientNet lies a thoughtful balance between model size, computational effectiveness, and precision to ensure superior outcomes are achieved across all areas. Operating on a well-categorized dataset of ocular scans specific to various diseases in ophthalmology helps this algorithm derive precise information from photos for accurate diagnosis purposes. The optimized network scaling approach employed by EfficientNet not only guarantees illness identification accuracy but also makes resource usage more efficient. Striking a favorable balance between computation demands and precision with its exceptional effectiveness and efficiency. EfficientNet emerges as an invaluable tool in the accurate identification and detection of ophthalmological illnessesenhancing the overall standard of patient care and therapeutic results.

Table 2. Summary of Deep Convolutional Neural Network Methods

Network	Advantages
AlexNet	Introduced deep convolutional neural networks for image classification.
VGGNet	Simple and uniform architecture. Easy to understand and implement.
GoogLeNet	Introduced efficient inception module for feature extraction andreduced parameters.
ResNet	Addressed vanishing gradient problem with skip connections and efficient for deep networks.
DenseNet	Dense connectivity enhances information flow and parameter efficiency.
MobileNet	Lightweight and designed for mobile/embedded devices.
EfficientNet	State-of-the-art accuracy with fewer parameters,balances depth, width, and resolution.

This section examines the most common retinal abnormalities, including glaucoma, diabetic retinopathy, age-related macular degeneration, and cataract. The next part of the section explores the imaging methods typically used for identifying and categorizing retinal diseases. Examining DR, AMD, cataracts, and glaucoma as particular abnormalities of interest was the main goal of this investigation.

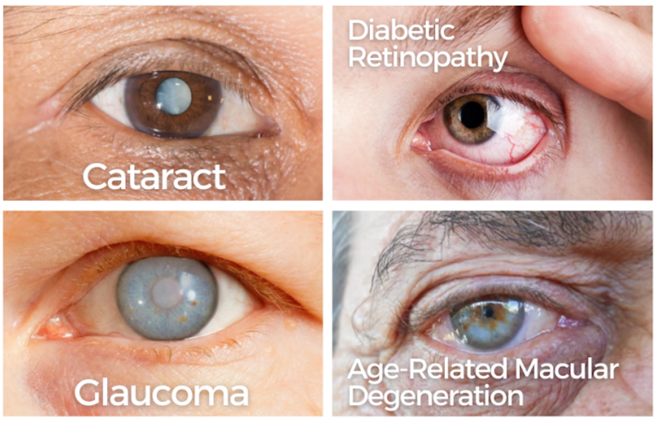

Figure 1. Major Eye Diseases

4.1.8 Cataract

Cataracts, a common retinal ailment, can cause the lens inside the eye to become opaque and reduce visual clarity. This condition is a significant cause of visual impairment and avoidable blindness worldwide, particularly among older individuals. The onset of cataracts is associated with aging, as well as other factors such as smoking and exposure to UV radiation. Detecting cataracts often involves a comprehensive eye exam that includes tests for visual clarity tonometry to measure eye pressure and a dilated exam to assess the condition of the lenses and other components of the eye. Surgical treatment is typically used for cataracts involving removing the opaque lens and replacing it with an artificial lens implant. There are various types of cataracts that can occur including age-related cataracts, congenital cataracts, traumatic cataracts, and secondary cataracts related to other medical conditions or medications. The classification of cataracts depends on the location and appearance of cloudiness within the lens[24]. A suggested method for grading achieves up to 92.66% accuracy overall and up to 93.33% maximum accuracy[25]. This suggested method proves superior in accurately classifying and rating cataracts compared to current techniques by at least 1.75% in accuracy. In addition to its use in analyzing slit lamp pictures for pediatric cataracts, DL has also shown promise in activities such as grading severity measuring density and identifying specific locations of pediatric cataract formation compared to pediatric ophthalmologists' performance using a convolutional neural network (CNN) algorithm. This demonstrates how DL has the potential to be an effective technique for the precise assessment and diagnosis of pediatric cataracts.

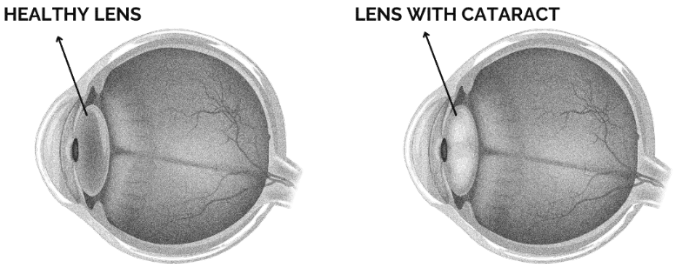

Figure 2. Cataracted Lens vs Normal Lens

4.1.9 Glaucoma

DL has been extensively studied in glaucoma research to determine its potential application in various testing techniques including optic nerve pictures, OCT, and vision fields. The clinical assessment of the optic nerve involves examining factors such as the cup-to-disk proportion, central neuro-retinal rim changes, peripapillary nerve fiber layer, disc hemorrhages, and vascular changes. Convolutional neural networks (CNN) have been used to develop an algorithm for diagnosing glaucomatous optic nerves based on clinical evaluation. This algorithm achieved impressive area-under-the-curve (AUC) values of 0.831 and 0.887 on two different databases[31, 32]. Modern glaucoma assessment primarily relies on optic nerve scanning with OCT. A combination of a single wide field OCT and innovative DL algorithms have proven effective in distinguishing between healthy individuals with early-stage glaucoma and those with the disease compared to the diagnosis provided by a glaucoma specialist. It outperformed the standard OCT parameters currently used for glaucoma assessment. Further research has demonstrated that DL is efficient in accurately segmenting the retinal nerve fiber layer in OCT images of the optic nerve head. This DL-based method successfully distinguished the retinal nerve fiber layer with an accuracy rate of 92% ± 2.3% sensitivity rate of 90% ± 2.4% and specificity score of 0.95. These findings highlight its usefulness in separating OCT images for optic nerve investigation[33]. The ResNet-50 model's accuracy in classification is 90%, with 42% for sensitivity and 94% for specificity, and the receiver operating characteristic (ROC) curve's area under the curve is 0.84. Similar results are shown by the GoogLeNet model, which has an area under the ROC curve of 0.91, an accuracy in classification of 91%, a sensitivity of 17%, and a specificity of 98% [9]. These performance indicators show how accurate and successful both algorithms were at classifying data.

Table 3. Summary of DL Methods for Cataract Detection

Reference	Year	Acc	Sp	Sn	AUC	Network
[26]	2020	95.65	0.96	0.95	0.97	SVM
[27]	2020	95.7	0.98	0.94	0.94	DCNN
[28]	2020	87.6	0.97	0.80		ResNet-101
[29]	2021	97.66	0.98			ResNet-50
[30]	2021	97.39	0.97	0.97	0.97	CRNN
[29]	2021	99.13	0.99			CNN

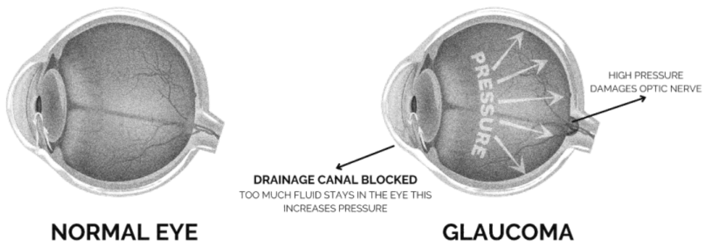

Figure 3. Glaucoma Lens vs Normal Lens

4.1.10 Retinal Disorders

Deep learning (DL) has been shown to be effective in detecting AMD and (DR) through screening and diagnosis in the field of retina. Notably, a recent AMD study used a deep convolutional neural network (CNN) to precisely score the severity of AMD based on images of the fundus. The bi-modal DCNN showcased superior performance on a test set containing 143 pairs of fundus and OCT pictures obtained from 80 eyes (20 eyes per group). It achieved an impressive accuracy of 87.4%, a high sensitivity of 88.8%, and a commendable specificity of 95.6%[21]. In the context of visual impairment, AMD emerges as a prominent factor and it becomes essential to identify this condition promptly for better outcomes. The effectiveness of existing treatments for DR in preventing or delaying vision loss is limited. Therefore it is crucial to adopt computer-based scanning systems with high efficacy for early detection on a regular basis. The present study has introduced fully automated diagnostic systems as an alternative to manual methods surpassing their performance levels significantly. By reducing the risk of misdiagnosis while also cutting down on time, labor, and expenses involved these new systems offer immense benefits in managing DR more effectively.

Table 4. Summary of DL Methods for Glaucoma Detection

Reference	Year	Acc	Sp	Sn	AUC	Network
[9]	2019	90	0.94	0.42	0.84	ResNet-50
[9]	2019	91	0.98	0.17	0.91	GoogLeNet
[34]	2020	94.1	0.93	0.95	0.99	ResNet-101
[35]	2021	97	1	0.94	0.97	DenseNet
[8]	2021	94.3	0.97	0.90	0.99	AlexNet
[32]	2021	96.5	0.8		0.95	MobileNet
[32]	2021	95.7	0.94	0.94	0.97	ODGNet

5. Discussion

After this study, we have clearly noted that in this modern era and increased workload, Deep learning techniques have helped ophthalmologists a lot in the diagnosis of different diseases. It can clearly be seen from Table 3, Table 4, and Table 5 that the accuracy is getting higher in the past years which clearly shows that AI is helpful and making diagnosis easier and accessible throughout the world. Now as the world has turned into a global village the patient and the doctor have access and ease to get diagnosed easily remotely over the world and all this is possible due to AI Deep learning techniques. Despite the numerous advantages associated with the implementation of deep learning (DL) in retinal disease detection, there are still several hurdles that need to be overcome.

There are obstacles that are linked to the DL approach. These challenges include difficulties related to image acquisition, model training, and the lack of interpretability in DL methods. Also, there is a little problem with the doctor which are not aware of the deep learning. This puts a gap here. Also, there is a certain limitation to the implementation of AI techniques. These limitations include restricted visibility of lesions, low image contrast, and noisy images, which often result in misdiagnosed abnormalities. Medical imaging classification and segmentation problems frequently suffer from an imbalance between positive and negative classes. Resulting in a biased classification that favors more common classes. However, there is still insufficient research conducted on the impact of imbalanced data on the performance of CNNs. Despite all these issues and obstacles, there has been notable progress, in the selection of appropriate pre-processing techniques to achieve satisfactory accuracy in AI deep learning techniques like CNN.

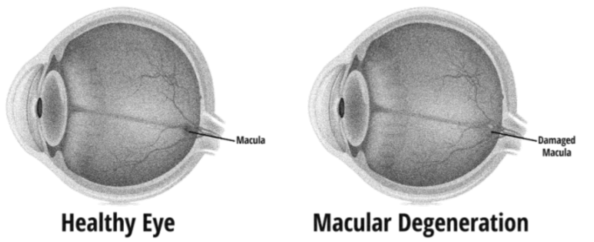

Figure 4. Healthy vs Damaged Macula

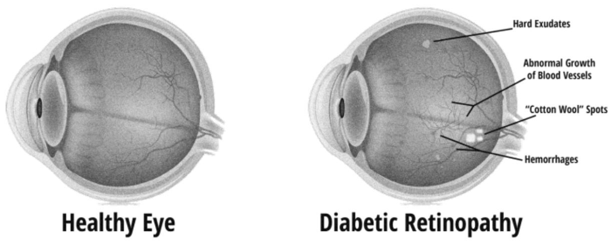

Figure 5. Healthy vs Diabetic Eye

Table 5. Summary of DL Methods for Retinal Diseases Detection

Reference	Year	Acc	Sp	Sn	AUC	Network
[19]	2019	80.8	0.86			CNN
[19]	2019	80.8	0.86	0.51		CNN
[23]	2019	81.9	0.97	1	0.99	DCNN
[10]	2020	91	0.94	0.87		VGG16
[36]	2020		0.91	0.92		AT-TENET
[37]	2021	82		0.64	0.96	DCNN
[38]	2021	98.7	0.98	0.99		CNN
[20]	2022	83.6				CNN
[20]	2022	86.9				CNN
[39]	2023	90.1	0.92			Efficient-Net

6. Conclusion

This systematic review explores various Deep learning techniques used in the diagnosis of ocular diseases. Specifically, the CNN and its further models are discussed in this paper along with their specifications. CNN has its good progress in image detection. These models aim to detect various ocular diseases with more precision and accuracy. The result of the image data provided shows that the AI Deep CNN techniques have several steps to detect specific diseases via the processing of the images. This study focused on the Convolutional-neural networks (CNN) further go with its models. Each model has its pros and cons. It is crucial to select the appropriate model to obtain the best suitable results.

Different diseases are discussed along with CNN and its suitable models. The research findings reveal an impressive degree of accuracy in identifying cataracts through the use of CNN achieving a remarkable 99.1%. Moreover, the model demonstrates a specificity rate of 99% highlighting its ability to specifically detect this eye condition. Similarly. When it comes to detecting glaucoma the CNN model shows promising results with an accuracy rate of 96% and a specificity rate of 80%. Lastly, CNN proves its efficacy in detecting retinal disorders as well boasting an impressive accuracy rate of 98% and a specificity rate of 98%.

There are certain limitations to the implementation of AI techniques. These limitations include restricted visibility of lesions, low image contrast, and noisy images, which often result in misdiagnosed abnormalities. Also the unfamiliarity with the Deep learning techniques used in the field. It is also visible from the results that accuracy is growing at a positive rate. In the future, it would be more effective and easier for doctors to deal with the technology.

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