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Ocular Disease Recognition Based on Deep Learning: A Comprehensive Review

Dilan Jameel Sulaiman[1], Adnan M. Abdulazeez[2]
dilan.sulaiman@dpu.edu.krd[1], adnan.mohsin@dpu.edu.krd[2]
[1]ITM Dept, Duhok Technical College, Duhok Polytechnic University, Duhok, Iraq
[2]Technical College of Engineering-Duhok, Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq

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Abstract

This review article represents a major advance in the field of medical imaging and ophthalmology by exploring the critical role of deep learning in the detection and diagnosis of eye diseases. Early and accurate diagnosis becomes essential due to the frequency of ocular disorders that pose a significant risk to vision, including diabetic retinopathy, age-related macular degeneration, glaucoma, and cataracts. The need for more reliable automated solutions is highlighted by the limitations of traditional methods, despite their benefits, which include reliance on small datasets and manual feature analysis. Deep learning, a subset of machine learning, is becoming evident as a powerful tool that can interpret complex medical images and improve diagnostic accuracy without the need to extract human features. This article explores the evolution of deep learning applications in ophthalmology, highlighting the difficulties encountered such as interpretability of models and data quality and the creative solutions that have been found to overcome them. We highlight the revolutionary impact of deep learning in eye disease detection through an in-depth analysis of recent developments, providing insight into potential future research avenues that may further improve patient care in ophthalmology.

A. Introduction

The eye is a sensitive and important part of the body because it picks up what is happening in a person's daily life and quickly sends this information to the brain so that the brain can react appropriately. The anterior and posterior fields of the human eye are two fused spheres that together form the oblate spheroid that forms the structure of the eye. Its three layers are shown in Figure1: the neurosphere (inner layer), the vascular integument (middle layer), and the fibrointegument (outer layer). The eye's many sensitive nerves and tissues make it vulnerable to pathological disorders and retinal disorders, which can impair vision. In a world of 7.33 billion people, about 36.0 million people are blind [1][2]. Diabetic retinopathy, age-related macular degeneration (AMD), cataracts, glaucoma, hypertension, and myopia are among the most common eye diseases [3]. Over 2.2 billion people are affected by eye diseases such as glaucoma, age-related macular degeneration and cataracts. The risk of complications is greatly increased by conditions such as long-term diabetes and cataracts, which are the leading causes of blindness globally, affecting more than 70 million people in addition to glaucoma [4]. Therefore, for many disorders to be effectively treated and recovered, early detection is essential.

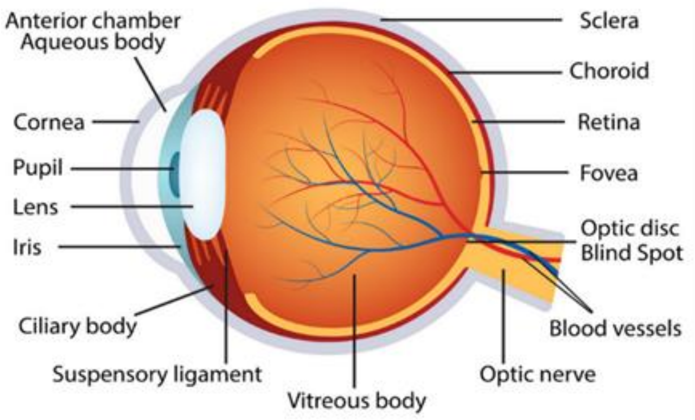


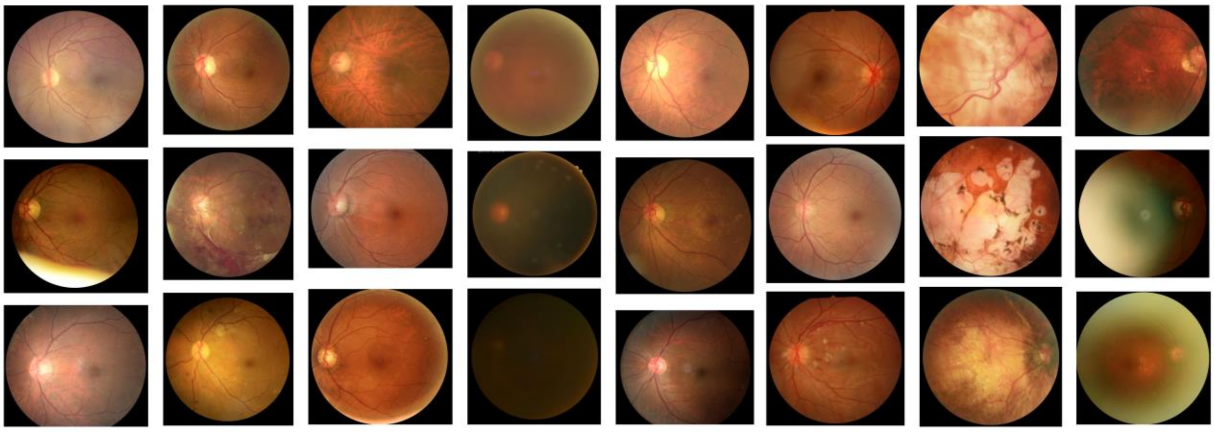
Figure 1. Anatomy of Human Eye [1].

This review examines the state of deep learning research in the field of eye disease diagnosis and examines the range of medical imaging techniques available [5][6]. It focuses in particular on retinal problems. Existing machine learning algorithms such as SVM, neural networks, Decision Trees, Naïve Bayes, and Random Forest are used in conjunction with small datasets of retinal images, setting limits to current methods for diagnosing eye diseases. Furthermore, current research mostly focuses on identifying one or two specific diseases, emphasizing the need to create a mechanistic model that can accurately identify a broader range of ocular disorders [7].

The remainder of this paper is structured as follows: Section II provides an overview of visual diseases. Section III discusses deep learning, while Section IV presents the applications of deep learning in diagnosing visual diseases. A summary of related works (Literature Review) is presented in Section V, followed by a related work table in Section VI. Discussion ensues in Section VII. Finally, the section concludes the paper and offers insights into future directions.

B. Overview of Visual Diseases:

The utilization of computer-aided diagnosis, a subset of artificial intelligence, for the purpose of early recognition of eye disease and prevention of vision loss is being explored [8]. The article covers the medical history of imaging methods used to identify retinal disorders and looks at a number of important retinal conditions, including glaucoma, cataracts and age-related macular degeneration [9]. The Figure 2 Offers a range of retinal scans for medical examinations, each of which shows a variety of eye health problems [10] Furthermore, current deep learning techniques for identifying ocular disorders are discussed, highlighting how important early and accurate disease detection is in enhancing patient outcomes and reducing condition severity [1]. MTRA-CNN presents a unique framework designed to use ancillary fundus images to diagnose glaucoma. This approach intelligently combines residual attention block and multi-stage transfer learning to overcome the drawbacks of insufficient data [11], greatly improving the performance of neural network features. Consequently, in comparison to conventional approaches, this methodology shows a considerable improvement in accuracy by allowing a more accurate and graded diagnosis of glaucoma [12]. A unique deep learning method is presented for early identification and classification of diabetic eye disorders in retinal images, including diabetic macular edema, glaucoma, and diabetic retinopathy [13] [14]. This technology seeks to improve the accuracy of disease localization and segmentation by combining Fast Region-Based Convolutional Neural Network (FRCNN) with Fuzzy K-Means ensemble. This would allow immediate treatment and prevent vision loss [10], assesses K-Means clustering on the Ocular Disease Recognition dataset for classifying eye diseases from fundus images, proving its accuracy and efficiency in disease categorization [15]. Moreover, Current advances in applying deep learning to optical coherence tomography (OCT) for diagnosing eye diseases, with a focus on diseases such as macular degeneration, glaucoma, and diabetic macular edema; It emphasizes the detailed, non-invasive imaging capabilities of OCT and addresses difficulties in integrating deep learning techniques for automated disease detection, such as issues related to data quality and model interpretability [16]. It offers deep learning technology that achieves good diagnostic accuracy even with small and diverse datasets for accurate detection of eye disorders using OCT images [17]. shows encouraging results for early diagnosis in ophthalmology using a deep learning model with ResNet50 and a multi-label classifier to reliably classify various eye disorders from fundus images [18].



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 2. Some samples of the (a) normal fundus and other seven abnormal cases, including (b) diabetic retinopathy (DR), (c) glaucoma, (d) cataract, (e) age-related macular degeneration (AMD), (f) hypertension, (g) myopia, and (h) other diseases [19].

C. Deep Learning:

Deep learning it has replaced traditional machine learning techniques due to its ability to automatically determine parameters from input data, which places it in the larger category of artificial intelligence and machine learning [20]. Highlights the potential of artificial intelligence to improve the efficiency and accuracy of eye care diagnosis by examining the role of artificial intelligence, especially deep learning, in ophthalmology [21]. In computer vision, deep learning (DL) has become the standard technique. Researchers looking to create novel algorithms for medical image processing to help with illness diagnosis and detection are paying close attention to DL. Different from traditional machine learning approaches, deep learning techniques do away with the requirement for manual feature development and analysis as well as lesion segmentation [22]. In deep learning, hybrid CNN-RNN models combine the classification accuracy of LSTM with the feature extraction capabilities of CNN to diagnose eye disorders from fundus images [23] [24]. This method highlights current advances in the use of deep learning for medical diagnosis, with the potential to significantly improve diagnostic accuracy, especially in the field of visual disease identification [25]. In addition, deep learning models such as VGGNet and DenseNet are being used to effectively diagnose cataracts from fundus images, highlighting the promise of deep learning to improve early identification and treatment of visual diseases [26] [27]. For accurate detection of cataracts in ocular images, deep learning models are used - CNN, Inception V3, and VGG-19. This highlights the effectiveness of neural networks in medical diagnosis, especially in ophthalmology [28]. A method for identifying ocular conditions that benefits from deep learning and a balanced and optimized dataset. It describes how to use preprocessed data analyzed by the model to identify problems such as cataracts, glaucoma, diabetic retinopathy, high blood pressure, age-related macular degeneration, myopia, and other eye diseases, or to classify the data as normal [29] [30], highlights the promise of machine learning in ophthalmology diagnostics by presenting ensemble deep learning models that achieve significant accuracy in detecting the stages of diabetic retinopathy and other eye diseases [31]. Using fundus images, the deep learning system was able to accurately diagnose the different stages of age-related macular degeneration (AMD) [32]. This method has the potential to automate and improve AMD management by enabling early identification and monitoring. This is a big step towards integrating machine learning and advanced imaging into eye healthcare, especially for disorders that need early intervention [33]. The study presents an ensemble deep learning method for eye disease detection that significantly improves accuracy and efficiency compared to individual pre-trained models. In figure 3 shows a flowchart of a system that recognizes eye diseases using a dataset that has been normalized using histogram equalization to train deep learning binary classifiers. By examining images of the left and right eyes, these classifiers can identify a variety of eye disorders, including myopia, cataracts, glaucoma, diabetic retinopathy, hypertension, age-related macular degeneration, and additional as-yet-unknown diseases [34]. Apply deep learning methods such as data augmentation and transfer learning, combined with color channel data, to increase the efficiency and accuracy of automated renderings[35].

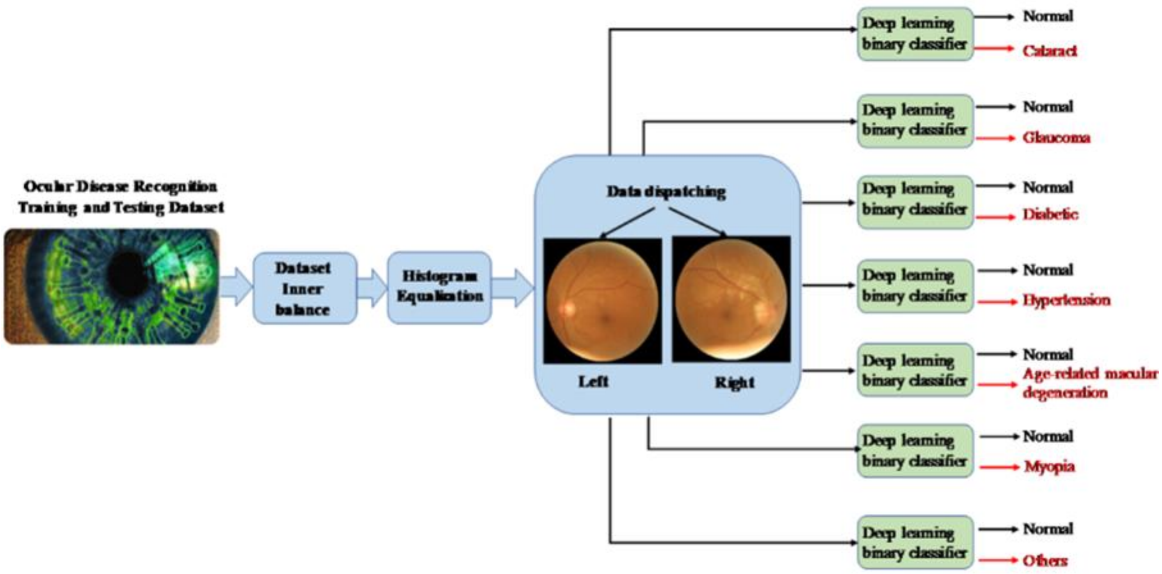


Figure 3. Multilabel parallel embedded proposed model's architecture [30].

D. Applications of Deep Learning in Diagnosing Visual Diseases:

Application of deep learning to classify retinal images for automatic recognition of cataracts. Research shows significant gains in cataract severity classification when using the Caffe framework to extract features from fundus images, resulting in greater accuracy than traditional techniques. This development highlights the potential of deep learning to improve ophthalmology diagnostic procedures, providing a viable pathway for early diagnosis and treatment of eye disorders [36], produces a deep learning system that uses models such as EfficientNetB7 to enhance and analyze retinal images in order to identify and classify diabetic eye disorders (DED). It shows improved prognosis of DED, which may lead to better outcomes for patients [37]. It presents a two-stage deep learning design that uses the ResNeXt101 model and data augmentation to improve cross-domain detection of eye disorders. This method greatly enhances the diagnosis of eye disorders in many data fields, demonstrating improvements in early retinal screening [38]. Describes a deep learning method that uses VGGNet and DenseNet models to diagnose cataracts using color fundus images [39][40]. With a classification accuracy of 97.94% for cataract, it demonstrates the potential for early diagnosis and reduces the workload associated with manual diagnosis [27]. In order to accurately classify and detect eye disorders early, the study uses ensemble models combined with deep learning techniques. These algorithms, trained on open databases, have the potential to improve ophthalmology diagnosis and reduce manual work [41]. Provides a multi-scale transfer learning method for glaucoma classification in retinal fundus images called the MTRA-CNN framework. Through a combination of mobile learning approaches and a novel multiscale strategy, it addresses the problem of detecting glaucoma across stages with insufficient data. This approach uses several datasets, such as ODIR and ImageNet, to enhance feature extraction capabilities for more accurate and progressive diagnosis of glaucoma [11]. In figure 4 shows a four-step deep learning model classification procedure for eye diseases: A pre-trained deep learning architecture receives an image dataset, which is subsequently split into training, validation, and testing phases to provide the final categorization of diseases like cataract [27]. Compares pruning and information distillation techniques with a focus on improving a CNN model for mobile visual user recognition. Knowledge distillation has been shown to successfully achieve a compromise between computational efficiency and accuracy for real-time authentication on mobile devices, especially with MobileNet-V2 and ResNet-20 [42].

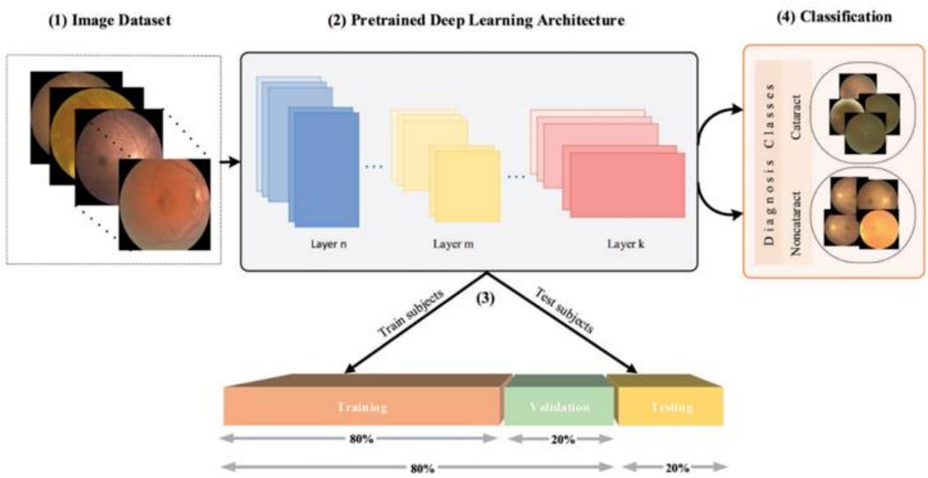


Figure 4. The block diagram of the proposed methodology [27]

E. Literature Review

In [43], the authors produced a deep learning-based system that uses retinal fundus images to classify diabetic eye diseases into mild and multi-class categories. Using pre-trained CNN models, their method was able to obtain up to 88.3% accuracy when using the VGG16 model. In order to increase diagnostic efficiency, the study used contrast enhancement, optimization, and fine-tuning. This has provided strong support for early detection and reduced the workload of medical experts.

In [44], the researches created an automated system for identifying eye diseases using facial images, deep learning and machine learning methods, with a focus on support vector machines (SVM) and deep convolutional neural networks (DCNN). With an average accuracy of the DCNN model of 98.79%, their technique significantly outperforms SVM in identifying seven eye disorders by analyzing visual symptoms. The aim of this system is to provide a readily available diagnostic tool that will be particularly useful in areas where there is no access to qualified medical experts.

In [10], the study presented a k-means fuzzy clustering and FRCNN-based automated detection and segmentation system for diabetic eye disorders. Their approach improves early detection by efficiently producing bounding box annotations for conditions including glaucoma, macular edema, and diabetic retinopathy. Comparisons were used to evaluate the effectiveness of the system and demonstrate its potential for automated eye diagnosis.

In [45], the authors achieved a recognition accuracy of 90.6% by developing a system that uses smartphone images and a modified DenseNet architecture to reliably classify ocular surface disorders. This method enables patients to perform self-examination with the aim of reducing the workload of ophthalmologists and improving accessibility for patients, especially for those who find it difficult to attend medical facilities.

In [46], the authors produced CataractNet, a deep neural network with an accuracy rate of 99.13% tuned to effectively recognize cataracts from fundus images, was created. Compared with traditional CNN models, CataractNet offers a significant reduction in computing overhead and enhanced training effectiveness by taking advantage of data augmentation and using fewer parameters. The potential for wide clinical application in early recognition of cataracts is highlighted by this development.In [27], the study achieved a diagnosis rate of 97.94% using a deep learning-based automated diagnostic system to identify cataracts using fundus images, VGGNet, and DenseNet. This study demonstrates how advanced neural networks can be used to identify cataracts early, which holds promise for improving diagnostics and providing automated solutions to help healthcare systems.

In [25], the writers constructed hybrid CNN-RNN models to categorize fundus pictures into retinal disorders, glaucoma, and cataracts by integrating LSTM networks with transfer learning. In order to overcome the class imbalance, the DenseNet169-LSTM model took advantage of improved data from the Kaggle dataset. It is worth noting that the model achieved an accuracy of 69.50%. This method demonstrates how successful hybrid models are in automating the classification of eye diseases, potentially improving the accuracy of healthcare diagnosis.

In [47], the researchers presented an automated method for detecting diabetic eye disease using DenseNet-100 and a custom CenterNet model. The system achieved 98.10% and 97.93% accuracy on the APTOS-2019 and IDRiD datasets, respectively. Their methodology far exceeded current techniques, indicating the effectiveness of deep learning in increasing diagnostic accuracy of eye diseases.

In [48], the creators established a deep learning model based on VGG-19 that can accurately detect eye diseases from fundus images with up to 98.13% accuracy. They resolved the imbalance in the data by switching from multiclass classification to binary classification. This method has greatly enhanced the identification of diseases including glaucoma, cataracts and myopia. Their research shows how deep learning can improve eye disease detection.

In [28], the authors utilized VGG-19, CNN, and Inception V3 to diagnose cataracts from eye examinations; VGG-19 had the highest accuracy rate of 95.87%. Their research shows how deep learning can be used to detect eye disorders early. The development of artificial intelligence has the potential to significantly enhance ophthalmology diagnosis and treatment plans.

In [49], the study developed DeepRetino, which uses CLAHE preprocessing and deep learning to accurately diagnose six eye disorders. Their approach, tested on the ODIR dataset, demonstrates how automated screening for retinal diseases can aid early detection. DeepRetino is a major step forward in the use of CNNs for eye health, offering improved diagnostic procedures for eye care practitioners.

In [50], the study presented a high-resolution technique for detecting eye diseases from retinal images by combining regression neural networks and adaptive mutation swarm optimization. In order to recognize diseases, their method preprocesses images, identifies important features, and segments them. This method provides a significant improvement in the accurate and timely identification of diseases such as glaucoma, diabetic retinopathy and cataracts.

In [22], the authors presented a multi-label CNN with an AUC of 96.7%, an accuracy of 94.3%, an accuracy of 91.5%, and suitability for identifying a range of eye disorders using fundus images. Their method worked better than previous models, proving to be useful for diagnosing eye diseases simultaneously. This development demonstrates how deep learning can be used to enhance eye healthcare diagnostics.

In [38], the researchers Provided a two-stage approach that combines deep neural networks and data augmentation to address difficulties in eye disease recognition across domains. By addressing the shortcomings of current models in a variety of clinical contexts, this strategy seeks to increase the accuracy and generalizability of fundus imaging screening.

In [51], the authors demonstrated the effectiveness of convolutional neural networks (CNNs) in diagnosing diseases almost flawlessly from retinal fundus images, with an accuracy rate of 99.85% in classifying eye disorders. This development demonstrates how deep learning can transform the early detection and treatment of eye diseases, preventing vision loss. Their research highlights how important technology is in improving the efficiency and accuracy of eye diagnosis.

In [52], the authors utilize the Ocular Disease Intelligent Recognition (ODIR) dataset, a convolutional neural network (CNN) model was created to classify six different eye disorders, significantly improving the diagnostic accuracy through hyperparameter optimization. The paper confirms how well the model performs in binary classification, with accuracy ranging from 98% to 100%. This shows how deep learning can be used to diagnose and treat eye diseases early.

In [53], the study examined deep transfer learning models with a focus on feature extraction and classification performance for diabetic eye disease prediction. They used a dataset of retinal images to show that the VGG19 model produced greater accuracy and accuracy. The results highlight the effectiveness of deep learning in automating disease diagnosis and suggest further improvements through sophisticated preprocessing and model modifications.

In [54], the writes investigated the effects of ocular disorders on iris recognition and found that individuals with severe uveitis had the most problems. The study, which included 54 patients, showed that Random Forest was the most effective and accurate diagnostic technique. This highlights how important iridotomy technology is in taking differences in eye health into account.

In [55], the researchers presented a multi-domain architecture that uses data augmentation, focus loss, and ResNeXt101 to identify eye diseases with better generalization. Their two-stage training significantly improved the diagnosis accuracy by adjusting the target domain after using a large amount of source data as a starting point. An AUC score of 0.974, an F1 score of 0.923, and a kappa score of 0.845 were among the achievements that demonstrated the effectiveness of the method across a range of data sets.

In [56], the researchers built a U-Net-based deep learning model to diagnose microbial keratitis, using data augmentation to increase the accuracy of sparse data. Compared with existing methods, their new approach produced higher diagnostic accuracy. The ability to early and effectively identify eye disorders has been improved through this research.

In [30], the authors created two deep learning models using the ODIR dataset and a parallel architecture to diagnose eye disorders. While the second model introduces new embedded deep learning networks, the first model uses VGG16 with transfer learning. Both models successfully detect myopia with a high degree of diagnostic accuracy. Their research may lead to improvements in automated diagnosis of eye diseases, and will also have implications for the Internet of Things and smart gadgets.

In [57], the study developed a convolutional neural network (CNN) with 89.9% accuracy to detect diabetic eye disorders. Their method automatically classifies retinal images in an effort to enhance early detection. This endeavor demonstrates how deep learning can improve ophthalmology diagnostics.

Their efforts should reduce pressure on ophthalmologists and enhance patient care.

In [58], the authors released Deep-Ocular, which used ODIR and RFMiD datasets to diagnose eye disorders with up to 95.13% accuracy. This was achieved by combining the improved AlexNet model with self-attention, dense layers, and XgBoost classification. The promise of ensemble learning and cutting-edge feature extraction in medical imaging is highlighted by this model.

In [37], the authors presented a deep learning framework that uses deep convolutional neural networks (DCNNs) to analyze enhanced retinal images in order to effectively recognize diabetic eye disorders (DEDs). Their research, which has achieved excellent diagnostic accuracy across multiple DEDs, holds great promise for improving diabetes care by enabling early detection.

In [7], the researchers put together a deep learning model that combines SqueezeNet with the Bottleneck Attention Module (BAM) to accurately identify and classify eye conditions such as diabetic retinopathy, cataracts, and glaucoma. Their model demonstrated the effectiveness of attentional processes in enhancing disease detection, with a high accuracy of 98.9% on test datasets and 98.1% in cross-validation. This study highlights how cutting-edge AI methods can completely transform eye healthcare diagnostics.

In [11], the study proposed MTRA-CNN, a multi-scale transfer learning system for glaucoma classification in retinal fundus images. This innovative method, which demonstrates the potential of cutting-edge neural network approaches in medical imaging diagnosis, significantly increased the diagnostic accuracy to 86.8% compared to methods without transfer learning through the use of multi-stage transfer learning and residual attention block.

In [59], the researchers applied deep learning, specifically ResNet50 and GoogleNet, to improve 98.5% accuracy in detecting the iris in eyes at risk for a variety of diseases. Their method of iris recognition through transfer learning highlights the power of deep learning to deal with the complexities of eye conditions. This development underscores the potential for more reliable and accurate biometric authentication in the medical field.

In [60], the authors used a deep transfer learning model based on InceptionV3 to detect age-related macular degeneration (AMD) from retinal images with 96.41% accuracy and 0.9633 AUC. Their method significantly improves early detection of AMD, proving the utility of deep learning in diagnosing eye diseases. This development offers a great advantage to increase the accuracy of ophthalmology diagnosis.

In [61], the authors examined both supervised and self-supervised deep learning models to identify eye diseases, and discovered that the performance of the self-supervised models was competitive. The present work confirms the effectiveness of self-supervised learning in augmenting eye disease diagnostic systems, which implies a great function of this methodology in increasing the accuracy and productivity of medical imaging.

In [9], the authors investigated deep learning models to identify eye diseases, especially applying the DenseNet121 model to classify medical images for healthy, diseased, and highly myopic eyes. The work aims to increase the efficiency and accuracy of eye disease recognition by automating diagnosis through deep learning, and to demonstrate the potential of these models in current medical diagnosis and telemedicine.

In [62], the researchers implemented IMoVR-Net, an advanced deep learning network that uses facial images to identify eye abnormalities in thyroid-associated ophthalmopathy (TAO). This network, which includes new algorithms for feature extraction and interpretability, demonstrates higher diagnostic accuracy, as measured by key performance metrics such as accuracy and an F1 score of over 87%. The effectiveness and transparency of IMoVR-Net diagnostics demonstrate its significant clinical usability.

In [63], the authors have been investigated using large-scale images to diagnose retinal disorders using deep learning; ResNet152 outperformed the other models, receiving a score of 96.47% at the American University in Cairo. Their work highlights the importance of deep learning in ophthalmology by showing how it can enhance eye diagnosis. The advantages of combining artificial intelligence with advanced imaging in healthcare are highlighted in this paper.

In [3], the study developed Fundus-DeepNet, a deep learning system that uses paired fundus images to diagnose various eye disorders. Extensive experiments on the OIA-ODIR dataset showed that its solutions outperformed existing models in terms of accuracy. This achievement demonstrates how Fundus-DeepNet can improve early recognition and treatment of diseases in the field of ophthalmology.

In [64], the authors demonstrated a model for eye disease recognition that uses deep neural networks with transfer learning and improved DS evidence theory. The notable metrics were 0.987 AUC and 92.37% accuracy. This model has demonstrated enhanced flexibility and accuracy in diagnosing various eye conditions. Due to its effectiveness, it may be possible to detect advanced eye diseases and plan treatment.

Table 1. Related Work Summary

Authors, year	Dataset	Methodology	Ocular Disease Type	Advantage	Disadvantage	Result/ Accuracy
Sarki et al., 2020 [43]	DRISHTI-GS, Messidor, Messidor-2, and Retina	CNN (VGG16, InceptionV3), Transfer Learning	Diabetic Retinopathy, Glaucoma, Diabetic Macular Edema, Cataract	High precision and useful for several classes	Needs a lot of work and an unbalanced set of data	VGG16: Multi-class 88.3%, Mild 85.95%
Akram A et al., 2020 [44]	1753 images, seven eye diseases	DCNN, SVM, PCA, t-SNE	periorbital cellulitis, conjunctivitis, trachoma, corneal ulcers, ectropion, and vitamin A deficiency-related Bitot's spot	Excellent precision, automatic identification	Requirements a big dataset	DCNN 98.79% with sensitivity 97%, specificity of 99%

Nazir et al., 2020 [10]	Diaretdb1, MESSIDOR, ORIGA, DR-HAGIS, HRF	FKM clustering in FRCNN	Diabetic Retinopathy, Diabetic Macular Edema, Glaucoma	Precise placement and effective division	Instruction requires Bbox annotations	Mean IoU of 0.95, mAP >0.94
Chen et al., 2021 [45]	953 smartphone images, 12 OSD types	Modified DenseNet, hybrid units	Ocular Surface Diseases (OSD)	Effectively, comprehensive screening by the patient	Uneven training sets and problems with images	Recognition accuracy 90.6%
Junayed et al., 2021 [46]	1130 images, augmented to 4746	Adam optimizer, deep learning, and CataractNet	Cataract	High precision and low computational cost	Unable to distinguish between different forms of cataracts	99.13% accuracy
Acar et al., 2021 [27]	5000 patients, Kaggle Ocular Disease	VGGNet and DenseNet, transfer learning	Cataract Diagnosis	Large dataset, excellent accuracy	Emphasizes accomplishments	VGGNet: 97.94%, DenseNet: 95.07%.
Londhe, 2021 [25]	Kaggle, 600 images, imbalance	CNN-RNN, InceptionV3, DenseNet169	Glaucoma, Retinal Diseases,Cataract	Integrates RNN's classification with CNN's feature extraction	The equilibrium of the dataset affects performance.	DenseNet169-LSTM highest, 69.50%
Nazir et al., 2021 [47]	APTOS-2019, IDRiD	Custom feature extraction from CenterNet and DenseNet-100	Diabetic Retinopathy (DR), Diabetic Macular Edema (DME)	High accuracy, efficient lesion localization	Restricted generalizability, dataset specificity, and computational complexity	APTOS-2019: 97.93%, IDRiD: 98.10%
Khan et al., 2022 [48]	ODIR, 5000 images, 8 classes	Binary classification, VGG-19	Myopia, Cataract, Glaucoma	Class imbalance resolved; accuracy was excellent	Retracted because of concerns regarding integrity. categorization that is binary as opposed to multiclass	VGG-19 accuracy: 98.13%, 94.03%, 90.94%.
Vayadande et al., 2022 [28]	5000 patients, fundus images	CNN, Inception V3, VGG-19	Cataract	Deep learning with high accuracy	Large dataset required	VGG-19 accuracy 0.9587
Zahra et al., 2022 [49]	ODIR, 5000 patients.	DeepRetino, CNNs, CLAHE	Detection of glaucoma, Cataract or Diabetic Retinopathy	Excellent precision and efficient preprocessing.	Confuses DR with normal images	Highest accuracy 99.74%
Subin et al., 2022 [50]	ODIR, 3200 images, 4 conditions	Hybrid AMSO and RNN (AED-HSR)	Cataract, Diabetic Retinopathy, glaucoma, Normal	Excellent sensitivity, specificity, and accuracy	Potential scalability and adaptability issues	Accuracy 98.08%, F1 score 98.67%

Ouda et al., 2022 [22]	RFMiD, 3200 images, 45 diseases	ML-CNN, three-phase method, normalization, and augmentation	45 ocular diseases, including DR, AMD	Reliable multi-disease identification and efficient enhancement	Restricted by size and dataset balance	Accuracy: 94.3%, Recall: 80%, Precision: 91.5%, DSC: 99%, AUC: 96.7%
Wang et al., 2023 [38]	OIA-ODIR, 10,000 fundus images	Two-stage, ResNeXt101, data augmentation	Gisorders of the general fundus picture.	Enhanced generalization between domains.	Complexity of readjusting the model	Kappa: 0.845, F1: 0.923, AUC: 0.974
Saini et al., 2023 [51]	Kaggle Open Repository images.	Convolutional Neural Network (CNN)	Cataract, Diabetic Retinopathy, Glaucoma, Normal.	High accuracy, nearly 4/5 cases	Needs more enhancement techniques	Accuracy rate of 99.85%.
Mostafa et al., 2023 [52]	ODIR, 6392 images, 8 classes	Binary classification	Glaucoma, cataract, diabetes, etc.	High accuracy, recall, precision	Not specified, focused on improvements	Accuracy 98-100%, Recall 97.99-100%.
Sharma et al., 2023 [53]	Kaggle, 5 types, color images	VGG19, NASNetLarge, InceptionV3	Diabetic Retinopathy (DR)	Excellent precision, automatic identification	Complex models, computational cost	VGG19 highest accuracy.
Asha et al., 2023 [54]	Kaggle, multiple ocular diseases	VGG-19, data augmentation	Various, including diabetes, glaucoma	Excellent precision and effective feature reuse	balanced data set is necessary	Proposed model accuracy: 0.9685
Wang et al., 2023 [55]	OIA-ODIR, 10000 images, age 30-80	ResNeXt101, data augmentation, focal loss	Various, for early screening	Solves cross-domain generalization issues	Off-site to train-site effect lower	Final Score improved by ~10%
Supreetha R et al., 2023 [56]	SLIT-Net and SUSTech-SYSU	U-Net, data augmentation	Microbial Keratitis	Performs better than cutting-edge, Dice total	Data imbalance and unaddressed image quality	DSC/F1-Score 0.977, Accuracy 0.985 (SLIT-Net); DSC/F1-Score 0.979, Accuracy 0.986 (SUSTech-SYSU) with Method 5
A Al Jbaar, et al., 2023 [30]	ODIR, 5000 patients, 10000 images	Two deep learning models using VGG16 and new networks for multi-label categorization.	Cataracts, moderate diabetic retinopathy, myopia, ocular hypertension, glaucoma, dry macular degeneration, etc.	Excellent precision, increased velocity, lower energy usage, appropriate for Internet of Things applications	Due to class imbalance, there is complexity in balancing the dataset for training	Achieved high accuracy of 0.9974 and 0.96 for Myopia detection.
Gupta et al., 2023 [57]	Over 4200 images, various conditions	Custom CNN, 19 layers	Diabetic Retinopathy, Glaucoma, Diabetic Macular Edema, Cataracts	Excellent exactness, automatic identification	Complexity in the identification of mild cases	Achieved 89.9% accuracy

Abbas et al., 2023 [58]	ODIR and RFMiD, various classes	AlexNet with attention, dense layers, ReliefF, XgBoost classification	Glaucoma, Diabetic Retinopathy, Cataracts, Normal eye-related diseases	Improved interpretability, high accuracy, and feature extraction	May have problems with invisible eye disorders	Accuracy 95.13%
Vadduri et al., 2023 [37]	IDRiD, Ocular, DRISHTI-GS, Messidor, Messidor-2	DCNN, ResNet50, VGG-16, Xception, EfficientNetB7	Cataracts, Diabetic Retinopathy, Glaucoma, Normal	Reliable multi-class DED categorization	Substantial and diverse training data is needed	Up to 98.33% for DR detection
Zia et al., 2023 [7]	ODIR, Glaucoma, Diabetic Retinopathy datasets	SqueezeNet, BAM attention module.	Cataract, glaucoma, diabetic retinopathy	Superb precision and efficient feature extraction	Potential adaptive challenges for emerging diseases	98.9% testing, 98.1% cross-validation.
Yi et al., 2023 [11]	Glaucoma fundus 4 classification, ImageNet, ODIR	MTRA-CNN, multi-scale transfer learning	Glaucoma, four stages	Improves feature extraction and makes use of several datasets	High processing expense for training in several stages	Best method accuracy 86.8%
Saleh et al., 2023 [59]	Warsaw BioBase V1, V2; CASIA V3	Deep learning, transfer learning, GoogleNet, ResNet50.	Multiple ocular diseases	Useful for treating eye diseases	Restricted by the influence of illness on division	ResNet50 best accuracy 98.5% (V1), 97.26% (V2)
Ogundokun et al., 2023 [60]	Kaggle OCIR, 5748 images, AMD/Normal	InceptionV3, deep learning through transference	Age-related Macular Degeneration (AMD)	Excellent precision and efficacious AMD identification	Limited to existing detection frameworks	Accuracy 96.41%, AUC 0.9633
Vijayalakshmi S et al., 2023 [61]	ODIR, 5000 individuals, diverse image resolutions	Self-supervised vs. supervised learning	Diabetes, glaucoma, cataract, AMD, hypertension, pathological myopia, etc.	Self-supervised learning has excellent efficiency and accuracy	Supervised learning need resource-intensive annotated data	Self-supervised model accuracy: 99.26%, Supervised model accuracy: 95.54%
Fu et al., 2023[9]	Alibaba Cloud, myopia: pathological, high, or normal	Deep learning, DenseNet121	Pathological, high, normal myopia	Excellent specificity and effective categorization	Not in contrast to the newest models	Validation accuracy up to 99%
Zhu et al., 2024 [62]	TAO datasets, 39,486 images.	Dilated convolution, DenseGabor, IMoVR-Net.	Thyroid-associated ophthalmopathy	Fine feature extraction and high interpretability	Model optimization complexity	Avg. accuracy: 87.8%, Sensitivity: 87.27%.
Nguyen et al., 2024 [63]	4697 images, 2006-2019 collection	Pretrained models, ResNet152, Vision Transformer, etc	Various retinal diseases	High AUC, detailed diagnosis visualization	Preliminary phase not systematically documented	ResNet152 AUC 96.47%

Al-Fahdawi et al., 2024 [3]	OIA-ODIR, 10,000 images, 8 diseases	Fundus-DeepNet, HRNet, Attention Block, SENet, DRBM	Eight types, including AMD, DR	Complete illness detection with excellent performance	Enormous and varied training data sets are needed	Off-site: F1: 88.56%, AUC: 99.76%. On-site: F1: 89.13%, AUC: 99.86%.
Du et al., 2024 [64]	ODIR-5K, 5258 images, 7 diseases	DNNs, ResNet50, ResNet101, ID-SET.	Glaucoma, Cataract, Diabetic Retinopathy, AMD, Retinitis pigmentosa, myopia, Normal	Decreased bias and increased robustness	Potential scalability and generalization issues	Accuracy: 92.37%, AUC: 0.987

F. Discussion

Table 1 focuses on how researchers have utilized various deep learning models to significantly improve the accuracy and effectiveness of diagnosing eye disorders. Traditional convolutional neural networks (CNNs) and more advanced designs such as ResNeXt and DenseNet are among the methods used in these investigations, and have played an important role in reaching diagnostic accuracy that often exceeds 98%. This high accuracy demonstrates how well models can extract features and classify diseases, which is important for a variety of disorders such as diabetic retinopathy and glaucoma. Despite these developments, research points to a number of continuing difficulties. The most important of these is the reliance on broad and diverse datasets, which are essential for building reliable models but are difficult to collect due to privacy issues and the rarity of some eye disorders. Furthermore, the computational needs of these sophisticated models pose major hurdles, especially in low-resource settings where they may have the greatest impacts. These problems are beginning to be addressed through innovations that reduce computing costs and power consumption, making the deployment of these technologies more feasible. The first step toward personalized medicine is the adoption of patient self-screening models, reducing barriers to access while simultaneously giving patients more control over their healthcare. However, balancing practical use and model complexity is a challenging task.

As the field progresses, ensure that these technologies are used ethically. One way to overcome potential biases in training data that may lead to differences in healthcare outcomes is to correct for them. If these systemic problems can be appropriately controlled, the rapidly developing field of deep learning application in eye disease diagnosis is poised to achieve major clinical progress.

G. Conclusion

The advent of deep learning has greatly advanced the detection and diagnosis of ocular illnesses, ushering in a new era in the discipline of ophthalmology. By automating the feature extraction process and offering improved illness detection accuracy, deep learning provides unmatched benefits over typical machine learning algorithms, as demonstrated by the careful assessment of current research and methodology. Advanced neural network models, like Convolutional Neural Networks (CNNs), combined with new techniques like multi-scale transfer learning and data augmentation have significantly enhanced the diagnostic performance for diseases like age-related macular degeneration, glaucoma, cataracts, and diabetic retinopathy. Despite the encouraging developments, the paper also identifies important hurdles that must be overcome in order to fully realize the promise of deep learning in ophthalmology. Important issues include the necessity of models that can be generalized across different patient demographics and imaging modalities, the availability of large annotated datasets for training, and the interpretability of the models. Moreover, it is impossible to ignore ethical issues and the requirements of legal frameworks to ensure the fair and safe application of AI in healthcare. Future directions in the deep learning have many different applications in detecting eye diseases. Clearly, collaborative efforts are needed to create large-scale annotated databases covering a variety of eye disorders at different stages of disease development. These types of tools will be useful not only to improve the training of deep learning models but also to validate and test them for their reliability and flexibility. Furthermore, investigating unsupervised and semi-supervised learning methodologies may mitigate the limitations imposed by insufficient data sets and difficulties in explanation.

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