Review of Eye Diseases Detection and Classification Using Deep Learning Techniques

Ahmed Aizaldeen Abdullah[1*], *Ahmed* Aldhahab[1] *and Hanaa* M. Al Abboodi[1]

[1]Department of Electrical Engineering, University of Babylon, Iraq

Abstract: Automated diagnosis of eye diseases using machine and deep learning models has become increasingly popular. Glaucoma, cataracts, diabetic retinopathy, Myopia, and age-related macular degeneration are common eye diseases that can cause severe damage. It is crucial to detect eye diseases early to prevent any potentially serious consequences. Early detection of eye disease is vital for effective treatment. Doing in-depth reading to identify any potential signs of eye disease is highly recommended. This paper will review all machine learning models built to detect and classify eye diseases in addition to helping grasp all limitations and challenges in this field. Recognizing eye diseases is a difficult task that typically requires several years of medical experience. This research is to be conducted to serve as a starting point for finding the most versatile solution. This research aims to review eye disease classification using deep learning models, including VGG16, ResNet, and Inception. The general classification model consists of these steps: The first step is to collect the globally obtainable datasets for the eye disease and pre-process them to ensure the generalization of experiments. The goal is to train the model to recognize disease symptoms instead of tweaking the outcomes for a specific dataset section. With the successful deployment of deep learning techniques for image classification and object recognition, research is now directed towards deep learning techniques instead of traditional handcrafted methods. One possible solution for the eye diseases classification challenge is to use a pre-trained deep CNN model for representation and feature extraction. This solution can be followed by classifier methods, such as support vector machines (SVM), multilayer perceptron (MLP), etc. It has been detected that CNN-based methods learned on large-scale marked datasets can be used for eye disease classification tasks with limited training datasets.

* Corresponding author's Email: eng976.AhmedAizaldeen@student.uobabylon.edu.iq

1 Introduction

Machine learning, artificial intelligence, and deep learning algorithms have played a major role in shaping the 21st century. These technical algorithms have been shown to aid individuals with a variety of eye disorders via precise diagnosis. To prevent further difficulties and disruptions to the eyes, it is of the utmost importance to detect early signs of eye disorders or ophthalmic diseases. When it comes to eye diseases, doctors typically rely on observational methods. However, this approach can be time-consuming and prone to human error, so it's crucial to incorporate machine learning and artificial intelligence algorithms thoroughly. This will ensure the safety of future complexions by providing appropriate clinical measures. Three subfields of artificial intelligence aim to mimic human behavior and intellect: general, super, and narrow [1].

Algorithmic and intuitive learning, conventional learning, smart sensing, robotics, and a natural language processor are all components of artificial intelligence. Nevertheless, ocular disease causes may be better identified with machine learning and its algorithms in medical treatments, machine reading, voice recognition, and writing recognition. The motivation for machine learning, however, has been noted to come from both deep learning and traditional ML. On the other hand, ophthalmology has been at the forefront of using deep learning, and machine learning algorithms to compute data from a variety of ophthalmic images to make a quick diagnosis of disease. It is reasonable to assume that these procedures will help detect diabetic retinopathy, glaucoma, and related ophthalmic complexions regardless of the presence or absence of physicians, professionals, or trained specialists, given current developments in the automated importance and applications of artificial intelligence, deep learning, and machine learning. The human eye is a complex and delicate organ susceptible to various diseases [2]. Globally, if these diseases are neglected, they will cause a significant problem, leading to loss of sight and other disasters. Some eye diseases may not cause harm, while others can lead to blindness and vision loss if left unattended [3]. It is possible to develop common eye diseases despite taking good care of the eyes. Most diseases begin early in life and get worse and more complex as they grow older. Common eye diseases are:

Diabetic Retinopathy (DR): Plasma glucose levels for patients that exceed 7.0 mmol/L are an indication of hyperglycemia. According to the World Health Organization [4], High blood sugar levels (hyperglycemia) can harm blood vessels, nerves, and vital organs like the kidneys, eyes, heart, and brain. Damage to the walls of blood vessels will cause complications that affect the retina, generating DR. Abramoff et al. [5] suggest that DR is a leading cause of vision loss in adults. Figure 1 illustrates the effect of DR on the human eye fundus.

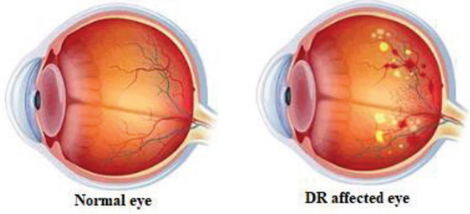

Fig. 1. Human eye fundus affected by DR [3].

Age-Related Macular Degeneration (AMD): This disease is a primary cause of blindness, affecting approximately 55% of legally blind Americans. This disease occurs when a person is 50 years or older, and due to this advancement, the macula deteriorates. The annual cost burden of AMD on the US economy is estimated at USD 30 billion. AMD is divided into Wet and dry AMD [6]. The problems of weakness or loss of vision are due to dry AMD. Wet AMD, which is also recognized as Choroidal Neovascularization (CNV), is the type that poses the highest risk for AMD. Figure 2 shows a retinal image demonstrating AMD.

Fig. 2. AMD.

Glaucoma: Glaucoma is a prevalent eye disease that can cause harm to the optic nerve of the eye. The high intraocular pressure here will cause blindness to the eye due to optic nerve damage of the eye. Figure 3 displays the impact of glaucoma on the fundus of the human eye [7].

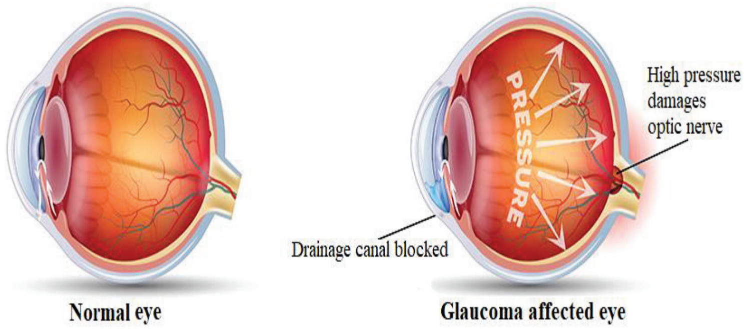

Fig. 3. Human eye fundus affected by glaucoma.

Cataracts: Cataracts are a common eye condition in which the lens becomes clouded, leading to impaired vision. It represents a significant disease that impairs vision and can be avoided worldwide, especially at older ages. This disease is associated with smoking, aging, and exposure to ultraviolet rays [8]. This disease is diagnosed through a comprehensive eye examination, including an assessment of the visual acuity, a dilated eye exam, and tonometry to evaluate the lens and other structures of the eye. The treatment course for this disease necessitates the surgical removal of the opacified lens, followed by the implantation of an artificial lens [9].

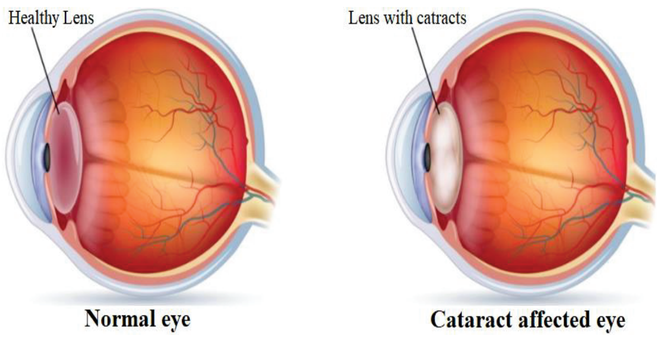

Fig. 4. Effect of cataracts in human eye fundus [10].

Myopia: Myopia is a medical condition in the human eye in which distant objects appear blurry and unclear, while near things are apparent and obvious. Presbyopia is the opposite of a process in which far objects appear more precisely than close objects. Astigmatism is a condition in which the eye's cornea is irregular, causing blurry vision at all distances. Another vision condition that typically occurs in people over 40 is Presbyopia. It involves the eye's ability affects the eye's ability to distinguish near objects.

2 Convolutional Neural Network and Deep Learning

CNNs are deep neural networks widely employed in DL to analyze visual data. Three layers make up CNN: the fully connected (FC) layer, the pooling layer, and the convolutional layer. The convolutional layer is the first layer, and the FC layer is the last. The convolutional layer of the CNN becomes more complex than the FC layer. When dots are joined in a specific manner, the result is a feature map, also known as a convolved feature. Unlike the convolutional layer, the pooling layer reduces the number of input parameters, resulting in some information loss. On the plus side, this layer makes the CNN more efficient and straightforward. CNN categorizes images in the FC layer based on the features of the previous levels. In this context, "fully connected" means that all inputs or nodes of the prior layer are linked to all activation units or nodes in the following layer [11].

Figure 5 below shows the basic eye disease classification process using deep learning, consisting of the following steps: data collection, pre-processing, feature extraction, and classification. The data collection gathers a diverse and well-annotated dataset of retinal images containing various eye diseases, such as glaucoma, diabetic retinopathy, and macular degeneration. Pre-processing plays a crucial role in DL for eye disease detection, as it helps prepare the data in a format that can be efficiently fed into neural networks. Here are the typical pre-processing steps for DL in the context of eye disease detection: Resize the images to a standard size to ensure consistent input dimensions for the CNN model, normalize pixel values to the range [0, 1], Augment the dataset using rotation, flipping, and scaling techniques to increase its size and diversity and split the dataset into training, validation, and test sets. A typical split ratio is 60-20-20, where 60% of the data is used for training, 20% for validation, and 20% for testing. Extract features from the retinal images using the CNN model. These features serve as input for classifiers. Then, Flatten or use global average pooling to convert the output feature maps into a vector for each image.

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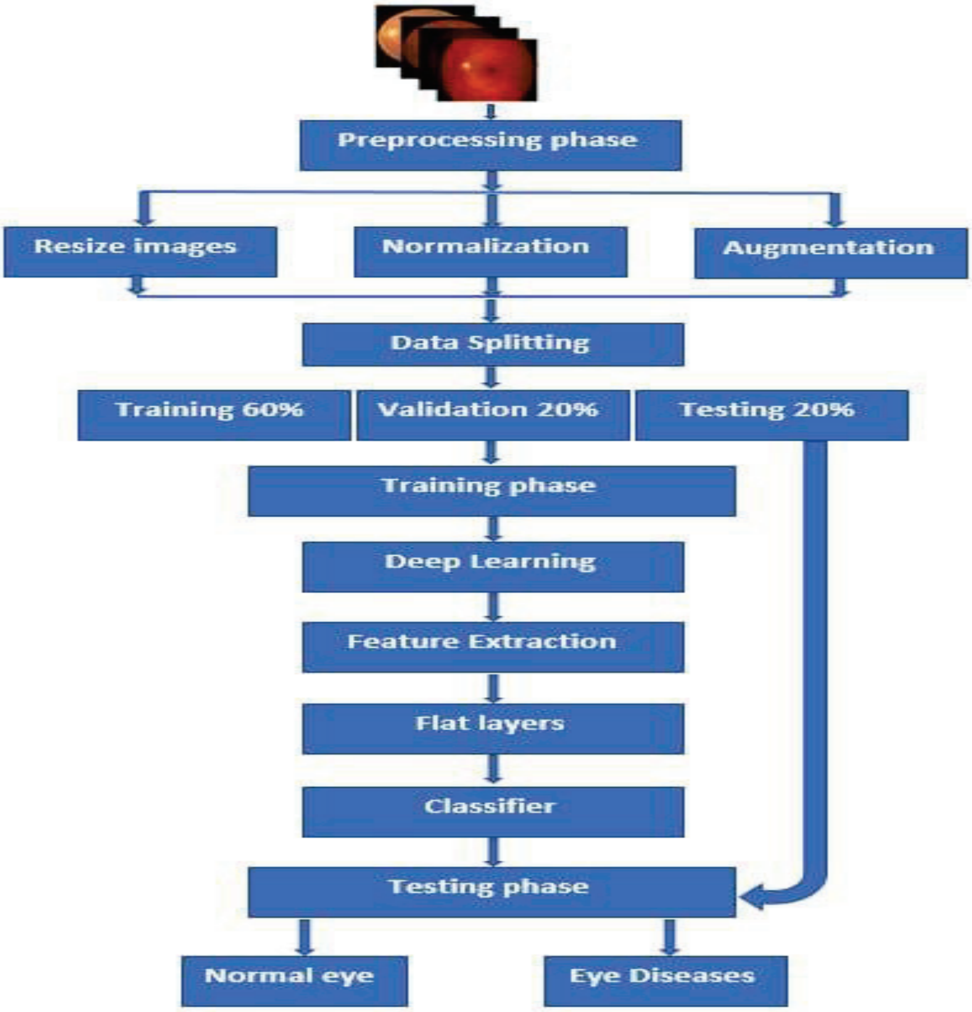

Fig. 5. Eye disease classification process.

3 Review of Eye Disease Detection Research

This section deals with previous work on eye disease detection and classification and the methods used through Deep Learning (DL) to detect them early to avoid blindness. The different eye disease datasets listed in Tables 1 to 4 are described below.

3.1 Diabetic Retinopathy Detection

Y. Wu and Z. Hu [12] used transfer learning and models such as VGG19, InceptionV3, and Resnet50. Disease was used. DR is caused by diabetes. Therefore, this article proposes a method for DR recognition using transfer learning. The experimental results show that this method's classification accuracy achieved 60%, better than the traditional direct. In [13], the authors present Distributed DL (DDL), Data Parallelism (DP), AND model parallelism (MP) to detect and classify DR. The gathered images are from the APTOS DR dataset available on

Kaggle. The MP strategy yields a higher validation accuracy of 62.13% and converges faster than DP strategies, whose validation accuracy is 55.72%. In [14], VGG-16, Inception-V3, and RESNet-101 models were used to detect diabetic retinopathy. The number of images equals 130 out of 110 DR and 20 typical regulars obtained from Kaggle. The final results show that this method's classification accuracy reached 73.52% for VGG-16, 74% for Inception-V3, and 81.28% for RESNet-101. After that, a deep CNN algorithm was described for classifying eye diseases, including Diabetic macular edema (DME) and Normal. The number of images was 3500, obtained from Kaggle (OCT image). The final accuracy of DME was 82% by the 5-Convolutional layer, and the Precision and Recall of the CNN model per DME class were 87%% and 74%, respectively. At the same time, the results of Normal achieved Precision and Recall at 77% and 89%, respectively [15].

A model proposed in [16] efficiently detects DR in real time. Early examination is critical to avoid problems with poor vision that lead to blindness in Kaggle. Seven hundred seventy-eight images were used for the training process, while 274 were used for validation. A total of 778 images were utilized for training purposes, whereas 274 images were employed for validation. A total of 778 images were used for training purposes, whereas 274 images were employed for validation. Based on the InceptionV3 model, the proposed CNN model achieved a validation accuracy of over 90%, with up to 5% improvement in testing accuracy. In [17], DR is currently considered one of the most challenging diseases caused by diabetes. This disease affects the retina and the blood vessels in the retina back, which causes poor vision and loss of sight and leads to blindness. The final results of accuracy were Sequential model 94%, VGG19 Architecture 73%, denseNet21 Architecture 81%, and SVM 87%. They focused on DL using transfer learning like ResNet-50 [18]. In this article, DR was used, and the images were obtained from the Kaggle website using two types of data: APTOS and EyePACS. The final result accuracy was 97.87%, and the Quadratic weighted kappa (QWK) score was 0.985. CNN used residual skip connection to segment exudates in retinal images [19]. Benchmark databases, E-aphtha, HEI-MED, and DiaretDB1, have 340 images. It is distributed as follows: 82 for E-aphtha, 169 for HEI-MED, and 89 for DiaReTDB1. The final results achieve sensitivity (0.97, 0.92, and 0.95) and accuracy (0.98, 0.99, 0.98) on E-ophtha, HEI-MED, and DiaReTDB1, respectively.

[20] proposed using DL based on a CNN called EfficientNet. This method is used to identify vision-threatening DR and Referable DR (RDR). The images from the Kaggle website include two public datasets, EyePACS and APTOS 2019. This proposal has considerably improved classification rates, accomplishing an impressive Area Under Curve (AUC) of 0.984 and DR AUC of 0.990 on the EyePACS dataset. Furthermore, the referable and DR categories achieved AUC values of 0.966 and 0.998 on the APTOS 2019 dataset. These figures demonstrate the successful application of our proposed approach and its potential to enhance the performance of relevant systems. In [21], the authors focused on classifying eye disease as diabetic retinopathy. The total number of images is 181,240 from Kaggle, including 135,930 for training and 45,310 for validation. The transfer learning algorithm was present, and three models were used: VGG16, VGG19, and NASNetLarge. The VGG16 model achieved 99.07% training accuracy and the most negligible loss (0.02).

Table 1. Diabetic Retinopathy Datasets.

SI. No	Study	Dataset	Diseases	Images count
1	[12]	Kaggle	Diabetic Retinopathy	
2	[13]	APTOS DR dataset	Diabetic Retinopathy	
3	[14]	Kaggle	Diabetic Retinopathy and Normal	130 images out of 110 of DR and 20 normal
4	[15]	Kaggle: OCT images	Diabetic macular edema (DME) and Normal	3500
5	[16]	Kaggle	Diabetic Retinopathy	778 images
6	[17]	Kaggle	Diabetic Retinopathy	
7	[18]	APTOS and EyePACS	Diabetic Retinopathy	
8	[19]	E-ophtha, HEI-MED and DiaReTDB1	Diabetic Retinopathy	82 for E-ophtha, 169 for HEI-MED 89 for DiaReTDB1
9	[20]	EyePACS and APTOS2019	referable diabetic retinopathy (RDR) and vision-threatening DR	
10	[21]	Kaggle	Diabetic eye disease	Total is 181240

3.2 Glaucoma Detection

Authors in [22] focused on glaucoma, which causes damage to the optic nerve and thus leads to loss of vision and blindness. In this study, two types of glaucoma datasets were used, which were obtained from the Kaggle website: RIM-ONE and RIGA. The number of queried images is 750 and 455 images, respectively. They were present in Transfer learning (TCNN) and semi-supervised learning (SSCNN and SSCNN-DAE). In the final result, accuracy results were obtained, with SSCNN-DAE reaching the highest performance of 93.8%, 92.4% for SSCNN, and 91.5% for TCNN. [23] discussed the effect of glaucoma on changing the thickness of the layers of nerve fibers in the retina, which leads to increased pressure within the optic nerve, which is considered an incurable disease. The ORIGA dataset was obtained from the Kaggle website, and the number of images in it reached 650. It included 168 images for glaucoma disease and 482 images for normal. The model was tested on 65 images and achieved an accuracy of 89%. The ResNet and Unet-based segmentation were presented in [24]. The dataset can be found in three folders: Fund As-Train-Val-Data, ACRIMA, and ORIGA. A set of 2662 images is used to detect the glaucoma. The model of glaucoma disease detection grounded on MDFHBA-ResNet-GRU demonstrated a higher F1-score of 24.1% compared to DCNNResNet-GRU (22.7%), ResNet-ResNet-GRU (22.7%), CNN-ResNet-GRU (25.7%), and Ensemble-ResNet-GRU (34.5%). In [25], three models were used to detect glaucoma: bidirectional recurrent DL model (Bi-RM), term memory (TM) technique, and linear regression algorithm (LR). A dataset of 3321 samples and 5413 unique eyes was utilized for the learning process, while 1272 eyes were reserved for testing. It has been observed that Bi-RM has a lower prediction error compared to LR and TM. Additionally, Bi-RM shows the lowest prediction in in-class prediction between the three methods.

Table 2. Glaucoma Datasets.

SI. No	Study	Dataset	Diseases	Images count
1	[22]	RIM-ONE and RIGA	Glaucoma	750 and 455
2	[23]	ORIGA dataset	Glaucoma	650
3	[24]	Kaggle	Glaucoma	Total of 2662 images.
4	[25]	dataset of 5413 3321 samples is utilized and 1272 eyes are used for testing	Glaucoma	4593

3.3 Cataract Detection

To facilitate the process of automating the detection of cataract disease, this research [26] proposed an enhanced version of Inception-v3, which receives rapid and accurate results from the image pre-processing techniques, particularly adaptive thresholding, used here. The number of images of 2508 in the training and testing dataset is 568. The model architecture and the recommended image preparation method ensure a high classification accuracy of approximately 95%. In [27], the authors utilized a hybrid DL technique, combining DenseNet and ShuffleNet, to extract features and perform classification. The Python platform is used to set up the experiments, utilizing databases like STARE, DRIVE, and HRF for retinal image analysis. The images were 28 of DRIVE, 30 of STARE, and 27 of HRF. The DRIVE dataset achieved a 99% accuracy rate, while the STARE and HRF datasets achieved 98% accuracy.

Table 3. Cataract Datasets.

SI. No	Study	Dataset	Diseases	Images count
1	[26]	Privat	Cataract and normal	training 2508 and testing is 568
2	[27]	DRIVE, STARE and HRF	Cataract	28, 30 and 27

3.4 Multiple Retinal Disease Detection and Rare Diseases

The research focused on detecting AMD, DR, glaucoma, and other retinal disorders in multiclass or multiclass, multilevel tasks, and rare diseases are reviewed in this area. [28] proved the efficiency of the CNN-Recurrent Neural Networks (CNN-RNN) model in various disease classification challenges. This article focuses on different eye diseases: Glaucoma, retinal, and cataracts. Multiple features are extracted by Transfer Learning models, InceptionResNetV2, DenseNet169, and InceptionV3. The research is conducted using the Kaggle dataset, which includes 600 images. The hybrid DenseNet169-LSTM model accomplished 69.50% accuracy, with 87.40% specificity and 69.50% sensitivity. Three deep learning models, CNN, Vgg16, and Inceptionv3, were used to evaluate them [29]. The data used was from Kaggle (I Challenge-GON Comprehension). The number of images used was 955 of several diseases, including Diabetic Retinopathy, Myopia, Glaucoma, and routine. The results were that Inception V3 provides better classification accuracy (81.00 %) than others. The authors in [30] extracted features from images and successfully identified them using convolutional neural networks (CNNs). Three hundred seventy-five photos were found for eye diseases, such as cataracts, glaucoma, uveitis, and crossed eyes. The effectiveness of utilizing transfer learning with pre-trained models like ResNet50 is demonstrated by the model's exceptional accuracy in diagnosing eye issues. Ninety-five percent accuracy was attained after five epochs.

[31] developed a DL CNN using Keras and TensorFlow frameworks in Python. The model was trained on a dataset of 1692 images of four eye diseases: Myopia, Diabetic Retinopathy, Glaucoma, and normal eyes. Various optimization techniques for DL have been discussed, including time-based decay, constant learning rate, exponential decay, step-based decay, and adaptive learning rate. Adam's adaptive learning rate method achieved 92.58% accuracy for the training set, while the validation set achieved 80.49%. [32] authors discovered that cataracts, glaucoma, and diabetic retinopathy are the leading causes of eye blindness. The many classification models available include logistic regression, SVM (Support Vector Machine), Decision trees, KNN (K-Nearest Neighbors), Random Forest, and backpropagation. Following that, image processing methods like grayscale, resizing, and power transformation are used for the fundus images. Finally, a single hidden layer, sixteen input neurons, and two output neurons that are either normal or damaged are used to create a deep CNN (DCNN). For DR, the detection accuracy was 91%; for cataracts, it was 90%; and for glaucoma-affected pictures, it was 86%. [33] proposed that early detection and treatment reduce the patient's suffering and prevent blindness. Therefore, a computerized system is needed to detect eye problems using the fundus images.

The EYENET model uses CNN to accurately predict five eye diseases—crossed eyes, bulging eyes, glaucoma, cataracts, and uveitis. The proposed network is optimized using the Adam optimizer. The total number of images was 383, obtained from the Kaggle website. The EYENET model achieved the highest accuracy rate of 92.3%. Suggested Convolutional Denoising Autoencoders (CDAE) and the GMD model [34]. Glaucoma, Myopia, and DR are used and obtained from the Kaggle website and iChallenge-GON. The number of images used was 2050 for fundus images and 655 for Synthetic images. Based on this work, the model's accuracy improved significantly from 89.84% to 92.82% in the training set and from 89.94% to 93.32% in the validation set. In [35], the design is suggested to train six profound learning neural networks (DLNN) with the names InceptionV3, ResNet152V2, DenseNet201, EfficientNetB7, InceptionResNetV2, and NasNetLarge to detect and classify AMD from fundus images. Using the Google Colab Pro platform, the transfer learning technique implements the training process with AMD images. According to the examinations, DenseNet201 has the highest overall classification accuracy of 88% using the testing dataset for the three classes of AMD classification (Normal, Dry AMD, and Wet AMD). Moreover, the highest accuracy results for the inferred 2-class AMD classification (Normal vs. AMD) were from EfficientNetB7 and InceptionResNetV2, corresponding to roughly 95.06% and 93.5%, respectively. This work [36] focused on the transfer learning algorithm and models used MobileNetV3 and EfficientNetB0. The diseases focused on were diabetic retinopathy, glaucoma, typical, and cataracts. The number of images was 4,217, with 1074 standard files, 1098 files of diabetic retinopathy, 1038 files of cataracts, and 1007 files of glaucoma. The EfficientNetB0 model achieved an accuracy of 94%, while the MobileNetV3 model achieved 73% accuracy.

In [37], the authors presented CNN and transferred learning for eye disease classification to compare them to obtain the highest accuracy rating. This study focused on the following diseases: diabetic retinopathy, glaucoma, and cataracts. According to the Kaggle website, there are currently 4,200 adult images of these diseases. Transfer learning had the best results from CNN; the high accuracy achieved was 94%, while it reached 84% in traditional CNN. In [38], they introduced the GMD model to detect and diagnose eye diseases. They compared the three models, AlexNet, Inception-v3, and VGG16, with the GMD model for the evaluation performance model. The dataset of eye diseases includes four classes: Myopia, Glaucoma, Diabetic retinopathy, and Normal. The number of the used images was 2050 image. The final accuracy results showed that GMD has the best accuracy compared to other models, where accuracy was achieved at 95% for GMD, 92% for AlexNet, 92% for VGG16, and 94% for Inception-v3. Healthy, Cataract, Glaucoma, and diabetic retinopathy people were used and obtained from the Kaggle website [39]. The total number of images is 4217, distributed 1007, 1038, 1098 and 1074, respectively. The suggested methodology for experiments using a publicly available dataset resulted in an average Recall of 81.25%, Precision of 83.68%, accuracy of 95.17%, and F1 score of 79.12%.

[40] presented a flower pollination optimization algorithm (FPOA) that utilizes CNNs and multiclass support vector machines (SVMs). This study focused on cataracts, AMD, Glaucoma, and DR. The Precision, accuracy, specificity, recall, and F1 scores of 98.30%, 95.27%, 95.21%, and 93.3% were obtained for both the left and right eyes of 5000 patients. In [41], Long Short-Term Memory (LSTM) and CNN model networks have been utilized in this work. The eye diseases that were used here were obtained from the Kaggle website (DenseNet201 and Xception), which are diabetic macular edema (DME), choroidal neovascularization (CNV), and AMD. The number of images used was 7000 images. Using OCT images enhanced by GAN, DenseNet201 with LSTM achieves an accuracy of 0.969, a true-positive rate of 0.969, and a positive predictive value of 0.972. The Xception model with LSTM image captioning has a performance of 0.969, 0.969, and 0.938, respectively. In [42], this was used to diagnose several eye diseases, such as glaucoma, diabetic retinopathy, and cataracts. The main goal of this work was to use deep neural networks to automatically classify retinal fundus images into healthy and pathological categories. Convolutional neural networks (CNNs) were employed in our study to categorize retinal images according to their level of health. Following ten epochs of InceptionV3, MobileNetV2, Xception, and RetinalNet-500, the result accuracy was 97.30%, 97.30%, 96.45%, and 95.15% in that sequence.

[43] created 'UveaTrack,' a hybrid mobile application that employs deep learning (DL) structures, machine learning (ML) methods, and image processing techniques to enable the tracking of uveitis, an eye disease. Overall, the results from the "UveaTrack" program were superior and attained an average accuracy rate of over 85%. This work [44] uses the Optimal Deep CNN for Retinal Fundus Image5Classification (ODCNN-RFIC) model and focuses on AMD. Two types of datasets are obtained from the ESTAR and Kaggle ARIA Dataset. The ARIA dataset contains Normal class 61 images and 23 AMD class images. In addition, the STARE dataset has 45 AMD class images and 40 Normal class images. The ODCNN-RFIC method achieves maximal classification results with a 0.9778 sensitivity, 0.9888 specificity, and 0.9882 accuracy. [45] The STARE dataset utilizes approximately 385 retinal images of 14 ophthalmological disorders, including CRAO and BRAO. Five deep learning algorithms, EfficientNet, 3-Layers CNN, InceptionV2, ResNet-50, and VGG-16, are implemented in broad terms in this work. With an accuracy of 98.43%, macro averaged f-1 score, recall, and Precision of 98.37%, 99.16%, and 97.91%, as well as weighted averaged f-1 score, recall, and Precision of 98.50%, 98.43%, and 98.82% over batch size 64, EfficientNet had the highest performance.

Table 4. Multiple Retinal Disease Detection and Rare Diseases Datasets.

SI. No	Study	Dataset	Diseases	Images count
1	[28]	Kaggle	Cataracts, glaucoma, retinal and Normal	600
2	[29]	Kaggle	Diabetic retinopathy, Glaucoma, Myopia and Normal	955
3	[30]	Privat	Glaucoma, bulging eyes, cataracts, uveitis and crossed eyes.	375
4	[31]	Kaggle	Glaucoma, Myopia, Diabetic retinopathy and Normal eyes	1692
5	[32]	Privat	Diabetic Retinopathy, Glaucoma and Cataract.	
6	[33]	Kaggle	Bulging Eyes, Crossed Eyes, Cataracts, Glaucoma, and Uveitis	383
7	[34]	Kaggle	Glaucoma, Myopia, Diabetic retinopathy and Normal	2050 for fundus Images and655 for Synthetic image
8	[35]	Privat	3-classes AMD classification (Normal, Dry AMD and Wet AMD) and 2-class AMD classification (Normal vs. AMD)	1482 for 3-classes and 425 for 2-classes
9	[36]	Kaggle	glaucoma, diabetic retinopathy, normal and cataracts	4,217 files
10	[37]	Kaggle	cataracts, diabetic retinopathy, glaucoma and Normal	4200
11	[38]	Kaggle	Glaucoma, Myopia, Diabetic retinopathy and Normal	2050
12	[39]	Kaggle	Glaucoma, cataract, diabetic retinopathy, and healthy people	4217
13	[40]	(ODIR) database	age-related macular degeneration (AMD), cataract, diabetic retinopathy (DR) and Glaucoma	
14	[41]	DenseNet201 and Xception	choroidal neovascularization (CNV), diabetic macular edema (DME) and age-related macular degeneration (AMD)	7000
15	[42]	Privat	Normal, Glaucoma, Cataract and Diabetic Retinopathy	6000
16	[43]	Privat	Uveitis	
17	[44]	ARIA Dataset and STARE Dataset	AMD and Normal	ARIA include 84 images; STARE include 85 images
18	[45]	STARE dataset	Retina	385

4 Eye Disease Classification Challenges and Limitations

Eye disease classification using machine learning models has many limitations and challenges [15]. In the following section, these challenges and constraints will be discussed. In [29], the slight training set size limitation affects the model performance and decreases the classification accuracy. In [37], this model is a multiclass classification that classifies four classes of eye diseases. The main disadvantage of this work is that it had no pre-processing step that aimed to prepare the data for the classification step, which may have affected the model classification efficacy and accuracy. In [12], the primary limitations and disadvantages of the proposed methods presented in this work were the model's complex structure and the increasing number of epochs to around 300, which consume more training time and memory. In [20], the model consumes training time and memory due to its complex structure that requires 200 epochs and 64 batch sizes. In addition, the model lacks the hyperparameter, which may cause a lack of model evaluation data. In [25], the authors provided a less robust classification model due to training with low image quality. In [31], the work was based on learning rate analyzing and testing while neglecting the other model hyperparameters, which may significantly impact the model's accuracy. In [14], to overcome the VGG16 drawbacks and enhance the deep model accuracy, VGG-101 has been employed. Despite the complex structure of the VGG 101, which has 101 layers, it achieves better classification accuracy. In [41], this work can be further expanded by combining the manually created features with previously taught CNN deep features. The fused feature can then create a new training model for caption creation. According to the authors in [38], the most critical problems for any classification model are overfitting and overconfidence, in addition to the slow training process, and this paper suggested many ways to overcome and solve these issues. One possible solution to overfitting overconfidence and batch normalization issues indicated in this work was increasing the training data size and using a label-smoothing technique.

In [34], the system's efficiency is increased through more accurate algorithms and high-level training. The training data resolution can be increased by expanding the number of images in each class and combining many similar datasets [38]. Increasing the number of images with more training is required to achieve a more efficient system with higher reliability. The lack of ability to extract the disease's main features from unprocessed images without pre-processing or embellishment is one of the most critical problems that may seriously affect the classification mode performance [22]. It is needed to solve the problems and limitations of this technology and improve the performance of deep learning algorithms for classifying eye disorders [36]. Pre-processing steps must be updated, and many unlabeled retinal imaging data must be used with models based on deep learning [21]. In [16], the authors developed an ensemble-based model to improve detection precision.

Furthermore, the convolutional neural network can add more layers to extract a more significant number of features. An algorithm like this needs much more effort before it can be applied extensively [17]. The algorithm's accuracy could be increased by controlling the volume of training data. In [39], two main problems were presented. Due to the small training sample and the model's low performance, since the dataset is tiny, performance may be further enhanced by adding more data. Simultaneously, the AI method depends on pre-trained deep learning models that may not work well in environments with scarce memory. Feature selection is one of the primary solutions to the memory-consuming consequences. In [27], a robust feature selection algorithm is proposed to choose the best feature sets to improve the classifier. Enhancements can be made to improve the results, like data augmentation and applying different pre-processing techniques to remove noise from the provided dataset. In [18], the authors presented a model trained using all of the suggested strategies on a larger dataset, and the results were analyzed and compared to produce thorough research.

In [44], the ODCNN-RFIC approach that can maximize classification outputs using retinal fundus images has been presented. Hybrid DL-based classification models may be developed to increase the detection rate. On the other hand, the DL model performance may be enhanced by improved network architecture. In [43], the authors concentrated on improving their system to use text and image inputs correctly to classify eye disorders with comparable symptoms. In [30], their work required more images and training to increase the system's accuracy. Other works suggested that reducing color fundus images from larger dimensions to (224x224) pixel sizes is the constraint of current DLNN models for AMD classification. In [26], they were combined to create a creative, personalized algorithm that can be used to determine the pupil's area of whiteness, which contributes to our long-term goals.

5 Evaluation Measures

Many measurements are applied to evaluate machine learning models for classification and detection. Accuracy is a metric that assesses the classifiers using the test dataset. Using various evaluation methods helps to analyze the resulting data from different aspects and gives a better assessment and visual representation of results. In the following, the mathematical representation of different metrics involving Accuracy, Precision, Sensitivity, Specificity, and F1-score [46][47]:

$$Accuracy\ (ACC) = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \quad (1)$$

$$Recall\ (Sensitivity) = \frac{Tp}{Tp + Fn} \quad (2)$$

$$Specificity\ (SPC) = \frac{Tn}{Tn + Fp} \quad (3)$$

$$\text{Precision (PPV)} = \frac{Tp}{Tp + Fp} \quad (4)$$

$$F1 - score = \frac{2 * Tp}{2 * Tp + Fp + Fn} \quad (5)$$

A summary of several eye disease classification methods based on diseases found, datasets and models utilized, accuracy, Precision, F1-score, and recall are presented in Tables 5 to 8 and explained below. Deep learning techniques were employed in each research study to identify and classify different types of eye problems. While some researchers have utilized many datasets, others have only used one. Similarly, several works can identify several diseases, while others can only remember one.

Table 5. Summary of Deep Learning Methods for Diabetic Retinopathy Classification.

SI. No	Study	Model	Result
1	[12]	Transfer Learning, VGG19, InceptionV3 and Resnet50	accuracy achieved 60%, better than the traditional direct.
2	[13]	Distributed deep learning (DDL) and Data parallelism (DP) and model parallelism (MP)	The MP provides faster convergence and higher validation accuracy of 62.13% compared to DP validation accuracy 55.72%.
3	[14]	VGG-16, Inception-V3 and RESNet101	The Accuracy 73.52% for VGG-16, 74% for Inception-V3 and 81.28% for RESNet-101
4	[15]	CNN	The accuracy of DME was 82% by the 5-Convolutional Layer, and Precision and Recall of CNN were 87%% and 74%, respectively.
5	[16]	CNN (InceptionV3)	validation accuracy of over 90%, with up to 5% improvement in testing accuracy.
6	[17]	CNN	Accuracy was Sequential model 94%, VGG19 73%, denseNet21 model 81% and SVM 87%.
7	[18]	DL using Transfer learning (ResNet-50)	accuracy of 97.87% and Quadratic weighted kappa (QWK) score of 0.985.
8	[19]	CNN	accuracy (0.98, 0.99, 0.98) and sensitivity (0.97, 0.92, and 0.95) on E-ophtha, HEI-MED, and DiaReTDB1, respectively.
9	[20]	EfficientNET	Accuracy of 0.984 for RDR and 0.990 for DR on EyePACS dataset. While for APTOS 2019 dataset AUC of 0.966 and 0.998 for referable and vision-threatening DR, respectively
10	[21]	VGG16, VGG19 and NASNetLarge	The VGG16 model achieved 99.07% training accuracy and the most negligible loss (0.02).

Table 6. Summary of Deep Learning Methods for Glaucoma Classification.

SI. No	Study	Model	Result
1	[22]	transfer learning (TCNN) and semi-supervised learning (SSCNN and SSCNN-DAE)	Accuracy results with SSCNN-DAE reaching the highest performance of 93.8%, 92.4% for SSCNN, and 91.5% for TCNN.
2	[23]	CNN	Accuracy of 89%
3	[24]	CNN: Unet++-based segmentation and ResNet	The developed MDFHBA-ResNet-GRU-based glaucoma disease detection model proved better F1-score of24.1% than DCNNResNet-GRU, 25.7% than CNN-ResNet-GRU, 22.7% than ResNet-GRU and 34.5% than Ensemble-ResNet-GRU.
4	[25]	Bidirectional recurrent deep learning model (Bi-RM), linear regression algorithm (LR) and term memory (TM) technique	The total prediction error of the Bi-RM is significantly less than those of LR and TM.

Table 7. Summary of Deep Learning Methods for Cataract Classification.

SI. No	Study	Model	Result
1	[26]	CNN and Inception-v3	The accuracy of 95%
2	[27]	DenseNet and ShuffleNet	Using the DRIVE dataset, the accuracy of 99%, STARE dataset is 98%, and the HRF dataset obtains an accuracy of 98%

Table 8. Summary of Deep Learning Methods for Multiple Retinal Disease Detection and Rare Diseases Classification.

SI. No	Study	Model	Result
1	[28]	CNN-RNN models InceptionV3, InceptionResNetV2, andDenseNet169	The hybrid DenseNet169-LSTM model achieved the highest accuracy of 69.50%
2	[29]	CNN, Vgg16 and Inceptionv3	Inception V3 provides accuracy (81.00 %) than others.
3	[30]	ResNet50	The accuracy was 90.55% after five epochs.
4	[31]	Constant learning rate, time-based decay, step-based decay, exponential decay, and adaptive learning rate	The Accuracy 92.58% for training set and 80.49% for validation datasets respectively.
5	[32]	DCNN	Accuracy for DR 91%; cataracts 90% and glaucoma was 86%.
6	[33]	CNN	The EYENET model achieved the highest accuracy rate of 92.3%.
7	[34]	Convolutional Denoising Autoencoders (CDAE) and GMD model	The accuracy 89.84% in training set and 89.94% in validation set, to 92.82% in training set and 93.32% in validation set.
8	[35]	InceptionV3, ResNet152V2, DenseNet201, EfficientNetB7, InceptionResNetV2, and NASNetLarge	for 3-classes accuracy of DenseNet201 is highest 88% while for 2-classes the accuracy of EfficientNetB7 and InceptionResNetV2 about 93.5% and 95.06%, respectively.
9	[36]	MobileNetV3 and EfficientNetB0	The EfficientNetB0 model 94% accuracy and MobileNetV3 model achieved 73%
10	[37]	CNN and Transfer learning	The accuracy achieved was 94%, while it 84% in traditional CNN.
11	[38]	GMD model, AlexNet, VGG16 and Inception-v3	Accuracy was 95% for GMD, 92% for AlexNet, 92% for VGG16, 94% for Inception-v3
12	[39]	Deep learning	Recall of 81.25%, Precision of 83.68%, Accuracy of 95.17%, and F1 score of 79.12%
13	[40]	flower pollination optimization algorithm (FPOA) with CNN and multiclass SVM	The performance was precision, accuracy, specificity, recall, and F1 score of 98.30%, 95.27%, 95.21%, and 93.3%, respectively.
14	[41]	(CNN) models and long short-term memory networks (LSTM).	The Accuracy of 0.969
15	[42]	CNN	ten epochs of InceptionV3, MobileNetV2, Xception, and RetinalNet-500, accuracy was 97.30%, 97.30%, 96.45%, 95.15%, respectively.
16	[43]	Deep learning (DL), machine learning (ML)	the results were accuracy rate of over 85% on average.
17	[44]	(ODCNN-RFIC) model	*sensy* of 0.9778, *specy* of 0.9888, and *accuy* of 0.9882
18	[45]	EfficientNet, 3-Layers CNN, InceptionV2, ResNet-50 and VGG-16	EfficientNet performed 98.43% accuracy, f-1 score, recall, precision as 98.37%, 99.16%, 97.91%

6 Conclusion and Future Work

Automated screening techniques significantly reduce the time required for diagnosis, saving ophthalmologists time and money while allowing patients to begin treatment sooner. The manual analysis of retinal images is laborious, time-consuming, and subject to subjective evaluation. Additionally, there is a need for more ophthalmologists, particularly in developing nations, who are qualified to interpret the images. This paper offered an extensive overview of deep learning (DL) techniques for diagnosing retinal diseases. Among these, diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD), and cardiovascular disorders are the most common. If not identified on time, these diseases may result in irreversible blindness, which would be extremely difficult for people to deal with on a personal, family, and economic level, especially in developing nations. This paper examined the most recent automated deep learning-based methods for identifying and classifying eye diseases. We briefly reviewed deep learning techniques and detailed the publicly accessible standard fundus eye disease datasets. Because CNN is so effective, most research has selected it to identify and categorize images related to eye diseases. This review has also addressed valuable techniques that can be used to classify and identify ocular disorders using DL. CNNs have demonstrated a high degree of accuracy in identifying several retinal illnesses and the capacity to identify many diseases at once. One thing connected the techniques: they all discussed utilizing hardware resources. Most approaches prioritized performance over the complexity of the network. Almost every deep learning-based network had an issue with the lack of a theoretical basis. This is an issue with DL publications on medical image analysis generally. More study is required to assess how deep learning models work with CNNs on various datasets and populations. Future research in medical image processing could concentrate on both computer complexity and theoretical basis by contributing to the design and develop a hybrid model that combines the feature extraction capabilities of deep learning with the strong classification abilities of Ensemble learning algorithms to achieve high performance of accuracy, Precision, F1 score, and recall for classify many eye diseases so, applying a solid pre-processing, filters, and feature extraction to achieve ideal features for small image sizes, high resolution, and less storage. It reduces computational costs and time and reaches a less complex proposed system by utilizing pre-trained models, allowing for faster deployment and reducing the resources needed to train DL networks from scratch. Also, this paper explained all the limitations and challenges in this area and discussed all the possibilities to overcome them. Finally, all contributions in this work are essential for successfully deploying and practically applying the eye disease classification system in real-world medical scenarios and assisting medical professionals in early disease detection and treatment.

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