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A Survey on Classifying Ocular Diseases Using Deep Learning and Machine Learning Techniques

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ABSTRACT

In ophthalmology, using fundus images to identify ocular diseases early may pose challenges for clinicians. Manually diagnosing ocular conditions is time-consuming, difficult, and requires experimentation. As a result, technology was created to help computers differentiate between ocular diseases. It is possible to create a system of this type due to different learning algorithms based on visual capabilities. Recent breakthroughs in deep learning and machine learning have led to the development of intelligent systems that improve accuracy and efficiency in classifying eye diseases. The purpose of this study is to conduct a comprehensive survey of modern systems that classify ocular problems using different methods, including pre-trained deep learning networks, using the Ocular Disease Intelligent Recognition (ODIR) dataset. The goal is to build and train a model that can recognize and classify ocular disorders. Previous research indicates the increasing use of deep learning techniques. CNN-based methods have spread widely in this field, compared to traditional manual procedures, due to their outstanding results. The most prominent deep learning techniques are convolutional neural networks (CNNs), recurrent neural networks (RNNs), and various learning methods for increasing and transferring data. The survey highlights the potential of these systems to enhance classification accuracy and sensitivity while addressing challenges such as data availability, interpretability, and integration with clinical practice.

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1. Introduction

Many ocular diseases, including cataracts, trachoma, and corneal ulcers, can impair vision. Ocular disorders can only be prevented if they are detected early [1]. The retina is a light-sensitive layer of tissues located in the back of the ocular. It transforms incident light into neural impulses that are then processed by the brain. The visual cortex

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forms an image, which can be influenced by several illnesses that affect vision [2]. Ocular problems have become a major public health issue around the world. More significantly, this illness has the potential to cause permanent vision loss. Early diagnosis of these disorders in clinical settings can help to avert eyesight loss. Manual fundus examination can be time-consuming and labor-intensive, relying substantially on ophthalmologists' expertise. This issue makes large-scale fundus examinations to be more challenging [3]. Ocular surface disorders impact corneal, conjunctival structures, and adnexal gland functions [4].

These disorders, such as diabetic retinopathy, are major causes of blindness worldwide, leading to damage to the retinal vessels and neuroglia. The formation of saccular capillary aneurysms and loss of vesicles from capillaries characterize retinopathy. Endothelial cells, decreased perfusion, occlusion of capillaries, small arterioles, progressive thickening of the vascular basement membrane, and associated changes, including angiogenesis. Leakage, discharge, and bleeding. Early lesions may be difficult to identify. Early diagnosis and treatment can prevent or treat many causes. Delays in recognizing ocular diseases may lead to serious consequences. Many studies have found that the prevalence of blindness increases with a person's age. Modern life has expanded nowadays, as the use of digital screens greatly affects vision, which has led to an increase in cases of ocular diseases [5,6].

Furthermore, how ocular disorders manifest in different communities varies between developing and industrialized countries. Numerous countries, particularly in Asia, have significant rates of ocular morbidity that go untreated and underdiagnosed [7]. The rapid development of computer vision and digital technology images have increased the possibility of using image recognition for ocular diseases and the possibility of early diagnosis of the disease. Thus facilitating early treatment and improving clinical outcomes [8]. The employment of effective image processing algorithms improves it, enabling doctors in the initial diagnosis of the condition and allowing the patient to know the status of their ocular vision. Illness diagnosis is critical for reducing physicians' workloads. Medical facilities are continuously in need of electronic assistance to improve the accuracy of diagnosis for certain conditions. Computerization can assist with tasks such as large-scale data collecting, sophisticated input analysis, data structure and classification, relationship detection, and others. Machine learning and deep learning approaches can diagnose diseases without human intervention. Despite promising results, few studies have been successful in detecting a diverse variety of ocular disorders. Further research will be required to accurately diagnose numerous retinal diseases with fundus scanning [9].

2. Related work

This section covers several previous works in the field of ocular disease classification that have used the ODIR dataset and several machine and deep learning methods.

Lie et al. 2020 used color fundus images to automatically detect multi-marker eye disorders such as glaucoma, age-related macular degeneration (AMD), diabetes, hypertension, myopia, and cataracts. A dense correlation network (DCNet) was proposed to take advantage of dense spatial correlations. Between callers, DCNet consists of a basic convolutional neural network (CNN) and a spatial correlation module (SVM) and has achieved an accuracy of 93% [10].

B. Khanna et al., in 2021, stated that eye diseases can be categorized as diabetic retinopathy, glaucoma, age-related macular degeneration (AMD), myopia, hypertension, and cataracts. Across multiple classes and labels using a CNN based on transfer learning, They proposed four approaches to improve CNN models with pre-trained using the ODIR database. The VGG-16 network performs better than the CNN designs of ResNet, Inception V3, and MobileNet. The F-1 and AUC scores obtained with VGG-16 for two input methods using the Stochastic Gradient Descent optimizer were 85.57 and 84.93, respectively. Compared with alternative constructs, the Model 2 sequential insertion approach with the VGG-16 construct showed a slight improvement in AUC and F-1 score (68.88 and 85.57) with VGG-16 using the SGD enhancer [11].

Akanksha Bali et al. 2021 proposed a transfer learning technique for Multiclass, Multi-label data to forecast ocular disorders from fundus images, utilizing the One-versus-all strategy. Proposed transfer learning approaches can detect eight categories of anomalies on fundus images, including normal, diabetic retinopathy, cataract, glaucoma, age-related macular degeneration, myopia, and hypertension. Data was gathered and expanded from the Ocular Disease Intelligent Recognition Database (ODIR). These images were used in the VGG-16 network, and eight models were trained to classify each disease independently. With accuracy, it climbed from 89% to around 91%, as anticipated by the model. Significantly enhance disease recognition performance. The glaucoma prediction rate went from 54% to 91%, which is normal. The image prediction rate has grown from 40% to 85.28%. The disease prediction rate rose from 44% to 88% [12].

E. Sudheer Kumar et al. in 2021 proposed a novel Multi-Disease Classification diabetic retinopathy (DR), age-related macular degeneration (AMD), and Media Haze (MH)framework (MDCF) incorporating ensemble neural architectures. The dataset underwent preprocessing, which included contrast optimization, oversampling, scaling, and normalizing. The first stage involves photographing the fundus images to assess the likelihood of acquiring the condition. The second stage involves classifying numerous diseases based on the fundus images. Densenet201 and EfficientNetB4 neural networks were utilized for disease risk detection, with ResNet105 included for multiple disease classification. The suggested MDCF model was tested on the 2019 Ocular Disease Intelligent Identification (ODIR) dataset with an accuracy of 97.42% [13].

Saja Mahdi Hussein et al., in 2021, suggested an automated method for identifying patients with age-related macular degeneration using a CNN. This method is used to examine fundus images and extract detailed information from them. This method was used on the ODIR ocular illness dataset, and the images were divided into three stages of macular degeneration (early, moderate, and late) and the eye's normal state. The accuracy measures were employed to evaluate classification effectiveness, and the approach achieved 97% accuracy, 98.52% sensitivity, 89.29% specificity, and 93.9% area under the curve. These findings show that the suggested approach can accurately classify macular degeneration patients using fundus pictures and extract deep features with CNN [14].

Nouf Badah et al., in 2022, used machine and deep learning models to achieve autonomous detection of glaucoma disorder. K Nearest Neighbors (KNNs), Support Vector Machine (SVM), Naïve Bayes (NB), Decision Tree (DT), Multi-layer perceptron (MLP), and Random Forest (RF) are the six machine learning (ML) algorithms used for classification. Secondly, a deep learning (DL) model, like CNN, is based on the Resnet152 model. The (ODIR) dataset has been used to evaluate the proposed method. The gathered data showed that the MLP and RF classifiers had the best accuracy of 77% when compared to the other ML classifiers. Even more so for the same job and data set, the DL model (CNN model: Resnet-152) provides an accuracy of 84% using the same set of data and tasks [15].

Zainur Ahmad Chowdhury et al. 2022 suggested a system for diagnosing six diseases: diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD), hypertensive retinopathy, pathological myopia, and cataract with a 93.6% accuracy. The enhancement technique was used on fundus images, and deep features were extracted to increase performance with the darknet_19 network. This research uses and presents a support vector machine classifier for classification [16].

Wang et al. in 2022 proposed a multi-label classification ensemble approach for fundus images that uses CNN for direct detection of one or more labels of fundus disorders in retinal fundus images, which diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD), diabetes hypertension, myopia, and cataract. Each model is composed of two pieces. The first portion is the feature extraction network, which uses EfficientNet, while the proprietary neural classifier is designed for multi-label classification. Finally, recognition is achieved by combining the output probabilities from many models. The model was trained and tested using the dataset from ODIR 2019 (Peking International University Competition for Intelligent Recognition of Ocular Diseases) and achieved an accuracy of 73% [17].

Chellaswamy et al., in 2022, employed a deep convolutional neural network (DCNN) to detect cataracts, glaucoma, diabetic retinopathy, and age-related macular degeneration (AMD). The whale optimization algorithm is used to optimize DCNN's many hyperparameters. Retinal fundus photos from various databases were used, and the proposed optimization strategy improved accuracy by 8.1%. A multiclass support vector machine (MSVM) was utilized to classify the diseases listed above based on the DCNN output. The results showed that cataract detection accuracy was 96.4%, glaucoma 97.2%, DR 97.4%, and AMD 97.7% [18].

Saja Mahdi Hussein, in 2022, presented an automated technique that used a CNN approach to identify patients with age-related macular degeneration (AMD) based on images from the ODIR dataset. A convolutional neural network was used to extract deep features from the fundus images present in the dataset. A maximum classification accuracy of 99% was obtained [19].

Thavavel Vaiyapur et al., in 2022, presented an intelligent framework for diagnosing numerous retinal diseases (IDL-MRDD), utilizing deep learning algorithms and fundus images. The proposed methodology aims to classify color fundus images into many categories, including age-related macular degeneration (AMD), diabetic retinopathy (DR), glaucoma, hypertensive retinopathy, normal instances, and pathological myopia. To segment the image and correctly identify identifiable impacted areas, the scientists used the Artificial Plants method with the Shannon function-based multilevel thresholding (AFA-SF) technique. A SqueezeNet-based feature extractor was used to generate a series of feature outputs. In addition, a stacked autoencoder (SSAE) model was used to classify picture inputs for various retinal disorders. The model had an accuracy of 96.3%. This sophisticated framework improves the ability to diagnose and classify various retinal illnesses using fundus images. It helps to improve patient care and make rapid and accurate decisions in the field of healthcare [20].

Researchers Zahraa Najm and Abbas M. Al-Bakri 2023 combined descriptors to extract features and machine learning algorithms for classification in two approaches to classify diseases in the ODIR data set. The first used the NB method to attain the greatest accuracy of 75% in binary classification for the normal and abnormal categories. The classification was the second approach. Several investigations with various learning algorithms were conducted for the remaining six diseases: age-related macular degeneration (AMD), diabetic retinopathy (DR), glaucoma, hypertension, myopia, and cataracts, with the random forest (RF) algorithm achieving the best accuracy of 88% [21].

Sbai et al., in 2023, diagnosed three diabetes-related diseases: glaucoma, cataracts, and diabetic retinopathy, and compared four classification methods. Transfer learning was used to extract features from two different architectures, VGG16 and RESNET50, and the impact of variance-limited adaptive histogram equalization on model accuracy and precision was studied. Random Forest was used to replace the last layers during categorization. The models produced acceptable accuracies of 89.17% and 85.64% without using the variance-limited adaptive histogram equation. Still, they performed better when using the variance-limited adaptive histogram equation, with accuracies of 97.48% and 96.66% for VGG16 and RESNET 50, respectively [22].

Keya Wang et al., in 2023, proposed MBSaNet, a multi-stage fundus image classification model that integrates CNN and SA mechanisms. The convolutional block extracts local information from the fundus. The images SA module shows the complicated interactions between distinct spatial regions, therefore directly detecting one or more fundus diseases such as AMD, DR, glaucoma, hypertension, myopia, and cataracts in the retinal fundus images. Training and testing on the ODIR-5k dataset yielded an accuracy of 88.1% [23].

A. M. Mutawa et al. in 2023 classified diabetic retinopathy (DR) using four transfer learning models: Neural Network (CNN)-Visual Geometry Group (VGG) 16, Foundation Edition 3 (InceptionV3), Denisenet (121), Mobilenet. (V2). The models are also tested by combining images from three datasets from the Asia Pacific Teleophthalmology Society (APTOS), TOS, Ocular Image Archive Communications System (EyePACS), and Ocular Disease Intelligent Recognition. The model achieves the highest accuracy of 98.97% on collected images [24].

Aaron Berk et al. in 2023 utilized ResNet-152 to classify patient gender from fundus images. This network was fine-tuned by making the last layer a fully connected layer for binary classification, and two data sources were used: one private (DOVS) and one public (ODIR). The model was applied to a set of 2500 fundus images, yielding test scores with AUCs of up to 0.72 (95% CI: [0.67, 0.77]. These results show that the model can diagnose patients' genders using fundus images to detect diseases AMD, DR, glaucoma, hypertension, myopia, and cataracts with reasonable accuracy, as good gender discrimination was achieved. However, it is vital to highlight. An AUC score of 0.72 suggests that accuracy varies amongst models and that there is an opportunity for performance improvement in this area [25].

Xiaoqing Zhang et al., in 2023, proposed establishing an effective hierarchical channel unit of interest (EPCA). After building the channel, an EPCA-Net network was developed to automatically detect myopia in fundus images by stacking a series of EPCA units. Additionally, the recognition standard PM-fundus is created by gathering fundus images from ODIR datasets. The trials showed that EPCA-Net outperforms current approaches for recognizing myopia. The proposed model had an accuracy rate of 97.56%. [26].

Orhan Sivaz and Murat Aykut developed a comprehensive system for treating diabetic retinopathy, age-related macular degeneration, glaucoma, and cataracts in 2024. For deep learning architectures that integrate the EfficientNet backbone with the ML Decoder classification head, EfficientNet provides robust feature extraction with fewer parameters through complex scaling, just like ML Decoder. It increases speed and flexibility by converting the quadratic to linear dependency and implementing a group decoder technique. Additionally, the usage of Perceived Sharpness Enhancer (SAM) minimizes the loss value and loss unit. At the same time, more accurate results were obtained. Furthermore, EfficientNet's performance has improved significantly. The resulting model was evaluated on the publicly available Ocular Disease Intelligent Recognition (ODIR) dataset, which included 10,000 fundus images, and achieved an accuracy of 94.80% [27].

Amna Zia et al. 2024, presented SqueezeNet, an upgraded deep learning system, to identify multiple ocular diseases simultaneously, including cataracts, glaucoma, and diabetic retinopathy. This model included a bottleneck attention module (BAM) and an additional layer atop SqueezeNet. The method effectively recovers the most representative features from eye images while removing background elements that are not useful for illness identification. Datasets used for training and testing included ODIR, cataract, ORIGA, and glaucoma datasets. The method achieved 98.9% accuracy on the test dataset and 98.1% accuracy using cross-validation [28].

Usharani Bhimavarapu et al., 2024 developed a novel technical approach and categorization for hypertensive retinopathy (HR) cleaning. New spatial convolution module (SCM) mesh names have been added to extract interesting characteristics. ODIR, WINSPIREVR, and VICAVR databases were used, all of which are publicly available. The mild, moderate, severe, and malignant bands were then arranged using convolutional layers that were only applied once to the input fundus images. This procedure speeds up and shortens the processing time of vascular abnormalities. The SVM was upgraded and achieved the highest detection and classification success rate, with 98.99% accuracy. The ten individual classifications had the highest classification of five divisions, with the enhanced KNN classification reaching 98.72% [29]. A Summary of previous works about ocular diseases using the ODIR dataset is shown in Table 1.

Most previous researchers have faced several obstacles and challenges in diagnosing eye diseases using the ODIR (Ocular Disease Intelligent Recognition) dataset, including limited data size. Although the ODIR dataset is relatively large, it is still limited compared to the data required to train complex deep models. Restricted data may lead to poor generalization and bias in trained models. There is limited diversity in the ODIR dataset as it focuses on the Chinese population, which may lead to bias in models when applied to other populations. Therefore, more diverse data in terms of ethnicity is needed. And the geographic and demographic background of patients.

Another obstacle is that the quality of the images was heterogeneous, as the quality of the images in this data set varies because they were captured from different sources and with different devices. This variation in quality may affect the performance of the models and their ability to generalize. There is also a need for an explanation for deep learning models used to diagnose eye diseases, which can be complex and difficult to interpret. There is a need to develop methods to increase the interpretability of these models to achieve greater confidence in medical applications.

Table 1 - Summary of previous work that has used the ODIR dataset

Ref., year	**Diseases**	**Methods**	**Accuracy**
[10], 2020	Glaucoma, AMD, Diabetes Hypertension, Myopia and Cataract	A dense correlation network (DCNet) with SVM	93%
[11], 2021	DR, glaucoma (AMD), myopia, hypertension, and cataracts.	CNN models (VGG- 16, ResNet, Inception V3, and MobileNet)	85.57 % (VGG-16)

[12], 2021	Glaucoma, AMD, DR, hypertension, myopia and cataract	VGG-16	91%, 88%
[13], 2021	DR, AMD ,Media Haze (MH)	Densenet201 and EfficientNetB 4 with ResNet105	97.42%
[14], 2021	Age-Related Macular Degeneration	CNN (Convolution al Neural Network)	97%
[15], 2022	Glaucoma	Deep learning (CNN model: Resnet-152) and ML models (KNNs, SVM, NB, DT, M LP, RF)	84 % (CNN)
[16], 2022	DR, Glaucoma, AMD, Hypertensive Retinopathy, Pathological Myopia, Cataract	Darknet-19 will extract features with SVM for classification.	93.6%
[17], 2022	Glaucoma, AMD, Diabetes Hypertension, Myopia, Cataract	EfficientNet	73%
[18], 2022	cataracts, glaucoma, DR, and AMD	deep convolutional neural network (DCNN) with	96.4%, 97.7%

		(MSVM)	
[19], 2022	Age-Related Macular Degeneration	CLAHE and mean filter to preprocessing with CNN A to extract deep features	99%
[20], 2022	AMD, DR, Glaucoma, Hypertension, Myopia	SqueezeNet-based feature extractor, stacked autoencoder (SSAE) model	96.3%
[21], 2023	AMD, DR, Glaucoma, Hypertension, Myopia, cataracts	Machine learning algorithms NB, RF	75%, 88%
[22], 2023	DR, Glaucoma, cataracts	VGG16 and RESNET50 with random forest classifier	89.17% 97.48 %
[23], 2023	AMD, DR, Glaucoma, Hypertension, Myopia, cataracts	MBSaNet, a multi-level fundus image classification model integrating CNN and SA mechanism	88.1%
[24], 2023	Diabetic Retinopathy	transfer learning models VGG16, Foundation Edition 3 InceptionV3, Denisenet 121 and Mobilenet	98.97%
[25], 2023	AMD, DR, Glaucoma, Hypertension, Myopia, cataracts	ResNet-152	95%

[26], 2023	Pathological myopia (PM)	EPCA-Net network was developed to automatically detect myopia in fundus images by stacking a series of EPCA units	97.56%
[27], 2024	Age-related macular degeneration, cataracts, glaucoma, and diabetic retinopathy	ML-Decoder with the EfficientNet backbone	94.80%
[28], 2024	Cataract, Glaucoma, DR	Module BAM used with SqueezeNet	98.9%
[29], 2024	Hypertensive Retinopathy	New spatial convolution module (SCM), enhanced SVM, and KNN	98.99% 98.72%

3. Dataset Description

Peking University has made the Ocular Disease Intelligent Recognition ODIR-5K dataset available online as part of a grand challenge. This database contains 10,000 images, including the right and left oculars of 5,000 patients. The fundus images were acquired using several cameras with varying resolutions, including Kowa, Zeiss, and Cannon. Ocular doctors gave disease-specific tags to these images. Diagnostic keywords apply illness categorization labels to each pair of fundus images. The visual pathology dataset is unique. Unlike other freely available data sets, this dataset includes color fundus images of both oculars of a patient with single or multiple problems. The patient's age and gender are also included. The ODIR5K dataset presents additional challenges due to lesions associated with 12 distinct ocular disorders in other class images. Learning relevant features can be challenging in this scenario.

Additionally, the dataset is severely skewed regarding image count across eight classifications. These difficulties hurt the accuracy and performance of trained classification models. The ODIR-5K dataset presents a challenge for illness detection models due to many cameras and lighting conditions, making it more relevant to clinical circumstances [30]. This dataset contains eight cases of diseases:

3.1. Age-Related Macular Degeneration (A)

Age-related macular Degeneration(AMD) is the leading cause of vision loss, accounting for 54% of all legally blind Americans. AMD affects persons over 50 and is caused by age-related macula degeneration. The estimated annual cost burden for the USA The economic impact of AMD is USD 30 billion. AMD is typically preceded by the production of Drusen, which are little yellow fatty protein particles under the retina. There are two main types of AMD: dry and moist. Dry AMD typically causes gradual vision deterioration or loss. Wet AMD, also known as Choroidal Neovascularisation (CNV), is the most eye-threatening kind of AMD [31].

3.2. Glaucoma (G)

Glaucoma, which is predominantly a neuropathy rather than retinopathy, is caused by the loss of the optic nerve. This disease causes visual field loss. Glaucoma destroys the retina's ganglion cells and axons, and this occurs when the eye fluid (aqueous humor) does not circulate adequately in the front of the eye. Optical disc cupping is the hallmark of glaucoma. The visual representation of the optical nerve head (ONH) anatomy. Glaucoma is the third most common cause of vision loss, according to [32].

3.3. Cataracts (C)

Cataracts are a frequent retinal condition that causes clouding of the lens and impaired vision. It is a primary cause of vision impairment and preventable blindness globally, especially among elderly persons. The formation of cataracts is linked with age, as well as other variables, including smoking and exposure to UV radiation [33]. A complete eye exam, including visual acuity tests, tonometry, and dilated exams, is used to identify cataracts. Cataracts are often treated with surgery to remove the clouded lens and implant an artificial lens. There are numerous forms of cataracts, such as age-related cataracts and congenital cataracts [34]

3.4. Hypertension (H)

Hypertension affects the blood vessels in the retina and thus leads to damage to the retinal vessels. This can cause swelling, bleeding, and damage to the eye. Symptoms of hypertensive retinopathy include blurred vision, headaches, and double vision. According to this disease is highly progressive, affecting men more than women and 4-18% of the general population [35].

3.5. Pathological Myopia (M)

Myopia is a condition where distant objects appear hazy while nearby objects are distinct. Hyperopia is the reverse, in which distant objects appear clearer than nearby objects.Astigmatism happens when the cornea or lens has an uneven shape, resulting in impaired vision at all distances. Presbyopia is a disorder that affects those over 40, resulting in a gradual loss of the ability to focus on close objects. A full eye exam, including visual acuity and refraction tests, can identify refractive problems. Treatment options include corrective lenses (e.g., glasses or contact lenses) or refractive surgery (e.g., LASIK) [36,37].

3.6. Diabetes (D)

Diabetes is a chronic condition that requires ongoing medical care and other risk-reduction methods in addition to managing glucose levels. Ongoing diabetes self-management education and support are essential for empowering individuals, minimizing acute difficulties, and lowering the likelihood of long-term complications [38].

3.7. Normal (N)

The normal category of the Ocular Disease Intelligent Recognition dataset contains images of healthy oculars.

3.8. Other (O)

The category contains twelve visual diseases, which produces a categorization challenge and lowers the accuracy of the models. Samples of this data set can be seen in Figure 1.

4. Methodologies

This section introduces the main machine and deep learning techniques for ocular disease classification.

4.1. Deep Learning Techniques

Deep learning refers to machine learning techniques that work with neural networks that have multiple layers of neurons. Neural networks add depth to networks, allowing them to perceive intricate processes that non-deep equivalents cannot. Deep convolutional neural networks have attained the maximum accuracy in classification and object recognition tasks, occasionally outperforming human performance.ML methods rely on feature extraction procedures, which typically demand a lot of expensive processing (complicated design). Engineering features are tough, time-consuming, and require a high level of ability. A comprehensive classification, the model was created to classify the inputs using the extracted traits [39].

Deep learning techniques achieve autonomous feature engineering by combining feature extraction and classification in a single stage. The idea behind DL is to create more accurate ML algorithms with little or no feature engineering compared to traditional ML [40]. Another major difference between deep learning and machine learning is their accuracy as the amount of data increases. Deep learning algorithms work well for large datasets because deep learning requires a large amount of data to fully capture and learn from. On the other hand, traditional machine learning algorithms reach a saturation point with their handcrafted rules and no longer make any progress [41]. Deep learning methods are classified into four categories [42]: autoencoders, deep belief networks, recurrent neural networks, and convolutional neural networks. Figure 2 shows the various deep learning methods.

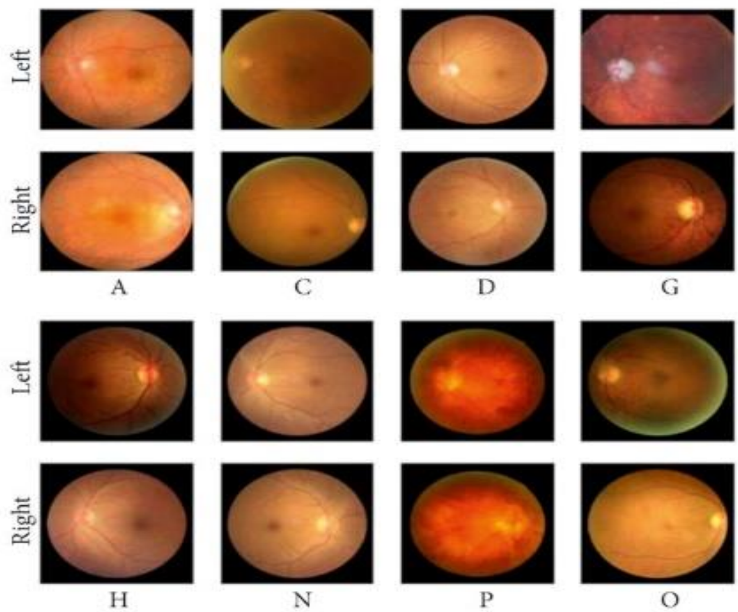

Figure 1: Samples of ODIR data set for left and right ocular images [30]

4.1.1. Convolutional Neural Networks (CNNs)

Convolutional Neural Network's capacity to recognize and interpret patterns makes it a solution to many computer vision challenges in artificial intelligence, including image and video processing. This pattern detection makes CNN suitable for image and video analysis, where it should perform well in detection, segmentation, and classification [43]. It is a specific sort of DNN that is regarded as one of the best neural network learning algorithms ever developed due to the difficulty of successfully training DNNs [44].

CNN is more than just a DNN with several hidden layers; it is a deep network that simulates how the brain's visual cortex analyzes and distinguishes images [45]. It employs various visualizations to assess image inputs and offer weights and learnable rules for separable regions of images. As a result, it makes use of local spatial coherence in the input images, allowing it to have lower weights in cases when some parameters are shared. They can be defined as structures with several stages, with inputs and outputs represented by sets of matrices known as feature maps [46]. CNN was founded by LeCun et al. [42] as a classification solution based on computer vision. CNN simplifies trainability by employing basic grouping and correction algorithms, as well as variance normalization. The term "convolutional neural network" is derived from "convolution," a specific linear process employed by the network. The convolution network has played a vital role in the advancement of machine learning, and it is a prime example of how ideas and information from understanding research are applied to machine learning applications [47].

A CNN's The overall architecture consists of two main components: a feature extractor and a classifier. During the feature extraction process, each layer receives the results of the previous layer as input and passes it to the next layer [48]. CNNs consist of multiple layers, each of which plays a specific role. CNN designs typically have three basic built-in layers: convolutional layers, pooling layers, and fully connected layers (FC). In classification/recognition tasks, the final FC layer is often associated with a classifier (such as SoftMax, a common linear classifier), which can then provide feedback on how the network responds to the input data. Each FC or convolutional layer has specific parameters/weights that need to be learned. There is a clear connection between the number of parameters per layer and the size of the multiple filters used. [49].

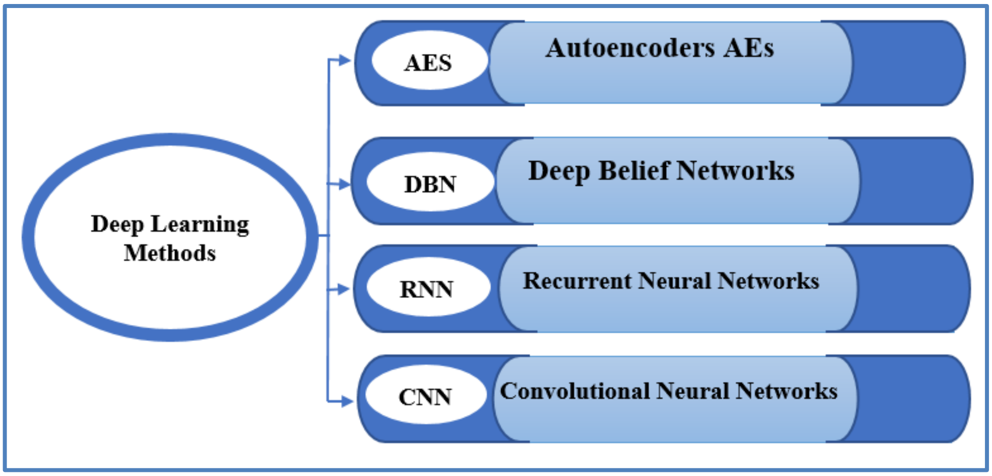

Figure2 : The categories of deep learning methods [42]

4.1.2. Pre-Trained CNN Models

Pre-trained networks are widely considered to be one of the most popular techniques in the field of medical image classification. They are trained on millions of publicly available photos from large datasets such as ImageNet for image recognition. These models can then be fine-tuned to perform new tasks without having to restart. In addition to gaining some advantages, the weights remain unchanged. There are many reasons for using pre-trained models. First, training complex models on huge datasets requires a lot of computing power. Second, training large models can take weeks, depending on the network design and training data. Finally, pre-trained models can help generalize the network and accelerate convergence [50]. There are many types of pre-trained CNN models, including AlexNet, ZFNet, GoogleNet, VGGNet, ResNet, DenseNet, and ResNeXt. [51].

4.1.3. Recurrent Neural Network (RNN)

RNN is another common deep learning method, particularly for NLP and speech processing. RNN differs from typical neural networks in that it utilizes sequential information in the network. This characteristic is crucial in applications where the data sequence contains useful information. RNNs provide temporal context and recurrent memory capabilities, making them suitable for classifications of eye variables that require dealing with temporal context and temporal sequences. They can be used to classify ocular diseases based on patient records, the evolution of symptoms, and examination findings over time. RNNs can be trained on the available data and improve their performance over time. The network's ability to classify ocular diseases can be improved by updating weights and coefficients across multiple training sessions, leading to Improved performance and increased accuracy [52].

4.2. Machine Learning Algorithms

Machine learning (ML) is a branch of artificial intelligence (AI) that allows computers to learn by exposing them to large amounts of data without explicit instruction. The basic goal of machine learning is to learn from a data set and reduce errors or increase the likelihood that a prediction is correct. Machine learning includes a variety of techniques for creating algorithms to process large amounts of data, as well as a variety of rules for achieving results. It also refers to the creation of fully automated machines and algorithms that operate according to a predefined set of rules. Machine learning is divided into supervised learning, unsupervised learning, and reinforcement learning. [53].

4.2.1. Support Vector Machines (SVMs)

In this phase, the SVM algorithm is used, one of the most widely used and efficient ensemble learning techniques and One of the supervised machine learning techniques based on statistical learning theory [54]. It selects a collection of characteristic subsets from the training samples to verify that the character subset's classification matches the dataset's division. The SVM has been effectively used in a variety of applications to solve classification problems. It offers a faster prediction time [55]. In such instances, SVM is a good method for modeling both linear and nonlinear interactions. In comparison to other nonparametric techniques, such as artificial neural networks, measurement time is rather short. Larger training data sets present a challenge in mechanical training, although SVM can still be generalized with less training knowledge [56]. Numerous researchers have studied and applied SVM in a variety of practical sectors, and it has been demonstrated that this classifier is capable of accurately predicting and classifying numerous cases [57].

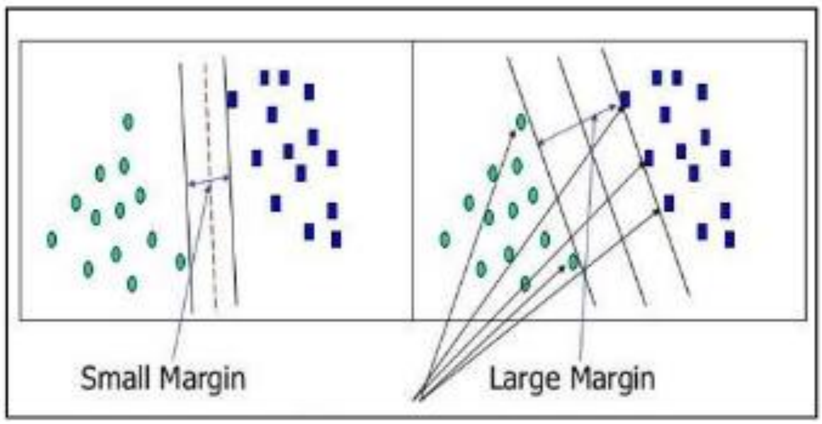

Figure 3: Boundary and support vectors. Left: A small buffer between two classes. Right: A wide boundary between two classes. [57]

4.2.2. Random Forests and Decision Trees

Leo Breiman's random forest is an ensemble of unpruned classification or regression trees built from randomly selected samples of the training data [58]. The induction process involves selecting random features to make predictions. The predictions of the ensemble are combined (majority voting for classification and average voting for regression). Each tree is carefully grown. N randomly selected samples from the training set are replaced with the original data. This sample is used as the training set for the tree. When splitting a node, a variable m less than M is chosen, and then m variables are randomly selected from M to achieve the optimal split. The value of m is kept constant, and each tree matures to its maximum capacity. Random forests consistently outperform single-tree classifiers such as C4.5. It has a lower generalization error rate than Adaboost, but is more resistant to noise. [59].

The concept of decision trees originated from the traditional tree structure, which consists of a root, nodes (where branches divide), branches, and leaves. A Decision Tree is made up of nodes (circles) and branches (connected segments). A Decision Tree is often drawn from left to right, beginning at the root and moving downward. The root node is the starting point for the tree. The "leaf" node represents the end of the chain. Internal nodes, or non-leaf nodes, can have two or more branches. A node represents a certain characteristic, while the branches represent a range of values. These ranges of values act as a partition point for the set of values of the given characteristic. The structure of a decision tree can be seen in Figure 4 [60].

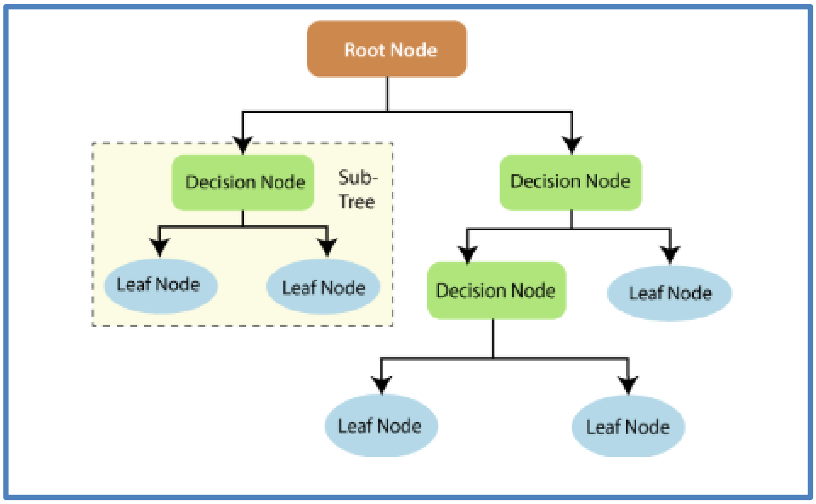

Figure 4: The structure of a decision tree [60]

4.2.3. K-Nearest Neighbors (KNN)

The KNN technique in pattern recognition uses the closest training samples to classify objects in the feature space. KNN is a type of instance-based learning or lazy learning that approximates functions locally and postpones computation until classification .The performance of a KNN classifier depends on the choice of K and the distance measure used. The estimated value is that the sensitivity of the size of K affects the radius of the local region, which is determined by the nearest neighbor distance of the query. Diverse K values lead to diverse conditional class probabilities. Small K values may lead to poor local estimates due to data scarcity and confounding patches. To improve the estimate, K can be increased, and a larger region around the query can be considered. Unfortunately, a high K value can overestimate homogeneity and lead to poor classification performance. Outliers from other classes cause poor performance [61].

5. Discussion

In this comprehensive survey of previous work in the field of ocular disease diagnosis and using the ODIR dataset, it was noted that many researchers have focused on developing automated learning models for the early detection of common ocular diseases such as diabetic retinopathy, glaucoma, myopia, and other diseases that cause blindness in some cases if not treated early, Designing models that rely on artificial intelligence can help in early detection of eye diseases and diagnose them faster and more accurately compared to traditional manual diagnosis. This issue leads to the possibility of therapeutic intervention at an early stage and reduces the time and effort expended by doctors and specialists in diagnosing cases. In general, deep learning and machine learning models in ophthalmology have great potential to improve health care and promote early detection and accurate diagnosis of eye diseases. Studies have proven that models based on artificial intelligence, such as deep neural networks, have achieved high diagnostic accuracy compared to traditional methods. The studies have proven that models based on artificial intelligence, such as deep neural networks, have achieved high diagnostic accuracy compared to traditional methods.

However, despite these positive results, there are still some challenges and research gaps in this field, the most prominent of which are:

- A larger and more common dataset is needed to represent different populations and disease patterns

- Develop models capable of better dealing with variations in image quality
- The possibility of integrating additional clinical information with visual data to improve diagnostic accuracy
- Verifying the generalizability of these models to different data sets. Ensuring diversity in training datasets and validating models across different populations is critical to developing globally applicable systems.

6. Conclusion

The focus of this research was on early identification and classification of eye disorders. Deep learning and machine learning techniques have shown great potential to accurately and reliably classify eye disorders. Despite ongoing obstacles, further research and developments in artificial intelligence technology, the use of multiple models, and training them on large data sets may overcome these obstacles and pave the way for their broader use in healthcare settings. Through previous research, it has been observed that deep-learning models. It has a high ability and efficiency in the field of diagnosing eye diseases. Based on this, it is expected that future research will continue to develop advanced artificial intelligence techniques to classify and diagnose eye diseases more accurately and reliably. These developments will contribute to improving health care outcomes for patients and accelerating early detection of diseases, as automated models are more objective and less prone to bias and errors compared to human diagnosis, leading to more accurate and reliable results. Also, integrating these technologies into healthcare systems can improve resource management and allocation. Better, leading to improved quality of care and reduced costs. Also, for this performance to be sustained, future research should focus on increasing data quality and availability, improving model interpretability, and ensuring generalizability. Diverse populations and facilitate their integration into clinical practice.

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