

A REVIEW USING DEEP LEARNING FOR OCULAR DISEASE DETECTION

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Abstract

Sight is the most important compared to all other senses because it is connected directly from eye to brain and helps to identify and recognize objects with ease. One of the most sensitive parts of the human body, it is susceptible to diseases such as glaucoma and Age-related macular degeneration. Computer-aided diagnosis is a branch of artificial intelligence that can aid doctors in identifying abnormalities. A brief medical background on imaging used to detect retinal diseases is provided in this paper, as well as details about some retinal diseases (Age Related macular, Cataracts, and Glaucoma). This also addresses the existing work on recognizing ocular diseases.

Keywords: computer-aided diagnostics Optical coherence tomography, fundus imaging, and convolution neural networks.

1. INTRODUCTION

Eye gathers information about events occurring in a person's daily life and transmits it to the brain in a fraction of a second so that the brain may respond appropriately, the eye is a vital and delicate part of the human body. The human eye's anatomy is shaped like an ablate spheroid and is made up of two merged anterior and posterior spheres, which are two modified spheres. Three coats are depicted in Fig. 1: an exterior fibrous coat, a middle vascular coat, and an inner nervous coat. Due to the large number of delicate nerves and tissue, there is a possibility that pathological or retinal illnesses might influence them and cause visual impairment. About 36.0 million individuals worldwide were blind as of 2015. There are 7.33 billion people on the planet. The World Health Organization states that changes that occur in lesions on the inside of the eye caused by either an internal or external source are the main causes of visual impairment and ophthalmological illnesses. There is also a chance of this can be attributed to a lack of timely and precise illness diagnosis. According to the World Vision Report, age-related macular degeneration, diabetic retinopathy, and glaucoma are the three main disorders that cause blindness.

When an ophthalmologist diagnoses a patient, they take into account the patient's symptoms, various retinal and ocular imaging, and a manual examination before reaching a decision that is time-sensitive. In the past few years, there were many applications of machine- Image identification, speech recognition, medical diagnosis, and predictive analytics are just a few of the tasks that can be performed with minimal human interaction thanks to machine learning. The availability of large volumes of data in the medical field offers a wide range of applications, and using artificial intelligence methods and algorithms in medical diagnosis can help a doctor identify the disease with the least amount of time and error. The review will include a brief overview of medical imaging, including the detection of ocular disorders and a few retinal diseases, as well as past deep learning research in this field.

II. MEDICAL IMAGING

For the identification of an ocular disease retina image is the input, it can be obtained using devices like Ophthalmoscope, Fundus Camera, Scanning Laser Ophthalmoscope (SLO), and Optical Coherence Tomography (OCT). These devices use different scanning methods such as Fundus imaging, Fundus Fluorescein Angiography (FFA), and Indocyanine Green Angiography (ICG). Fundus imaging is frequently utilized since it is a non-invasive and low-cost technique apart from this Optical Coherence Tomography (OCT) scan is used widely and these are discussed in the following sections.

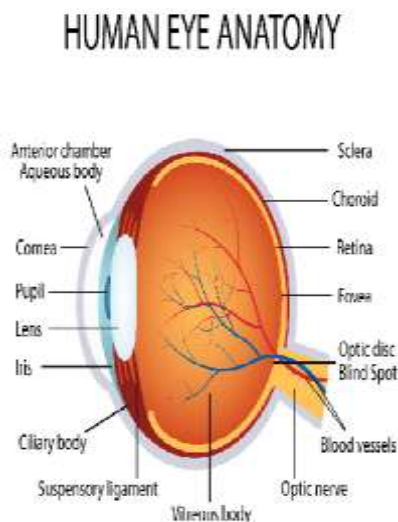


Fig.1. Anatomy of Human Eye

A. Fundus Imaging

The fundus picture, which consists of the optic disc, macula, vessels, and peripheral, is created by taking a back view of the eye using reflected light.

a) Optic Disk: A typical fundus optic disc is 1.5 mm in diameter, light pink in hue, and has a sharp edge. The physiological cup, a dip in the middle, is where the main retinal veins and arteries emerge. The ratio of height of the cup vertically to the optic disc height is known as the disc-to-cup ratio, and it typically ranges from 0.3 to 0.4 mm..

b) Macula: It is a highly sensitive area of the fundus, with great visual acuity and a large number of cones in the middle. It is also referred to as the yellow spot, measuring 5.5 mm and located on the temporal side. Its fovea, or center region, is where the object's Sharpe image is generated.

c) Periphery: The nasal, superior, inferior, and temporal retinal backgrounds are often where the basal glow is seen. The chorio capillaris beaming from beneath the retina is to blame. If anything, a thick presence in the vitreous cavity that might obscure the choroidal fluorescence from visibility would result in the fundal glow being absent, which is regarded as abnormal.

d) Vessels: Superonasal, Superotemporal, Inferonasal, and Inferotemporal are the four primary types of vessels that may be distinguished. These comprise arteries that are brighter, smaller, and exhibit a noticeable light reflex, as well as large, dark red veins.

Several general kinds of fundus imaging exist, including as monochromatic retinal photography, color fundus imaging, standard fundus photography,

B. Optic Coherence Tomography

A non-invasive imaging technique called optical coherence tomography (OCT) was created at MIT in 1991 and uses reflected light to produce images of the back of the eye. Compared to other methods, the optical coherence tomography (OCT) imaging system has the benefit of early diagnosis of retinal problems such as macular degeneration, glaucoma, and diabetic retinopathy. OCT pictures provide a cross-sectional view of the sub-retinal layers and can be utilized to diagnose illnesses at early stages. The Michelson-type interferometer, which consists of a low coherent light source, a mirror, and a detector, provides the basis for the OCT principle. A beam splitter first divides the light into two streams, one of which is directed into the human eye while the other toward the mirror. Together, the difference in the intensity of reflected light from both waves and the time delay produce a fading effect. It has been discussed in detail the principle of optical coherence tomography. Different types of OCT are based on the method of capturing the scans and the wavelengths of the source light, as will be covered below.

a) Time domain Optical Coherence Tomography: This is the first-generation OCT that scans all the retinal layers using monochromatic low coherence light and a time-based physical movement adjustment of the reference mirror. This results in a change in the optical length of the light. Because it detects each layer successively, this form of scan takes longer and increases the possibility of motion artifacts because of the patient's inattentiveness.

b) Optical coherence tomography in the spectral domain: This is a second-generation OCT that falls within the Fourier domain. In contrast to the TD-OCT, the reference arm's position is fixed and produces a spectrum of backscattered light using a broad light source. All of the backscattered light is detected once by a high-speed spectrum analyzer, and all of the scans will go through Fourier transformation, which is software that divides the composite waveform produced by collecting backscattered wavelengths into individual frequencies. This results in multiple axial scans. This kind of scanning has a speed of 18000–70000 axial scans per second and is often less time-consuming since it detects numerous layers of the retina in one go.

c) Swept Source Optical Coherence Tomography: It is also known as Time encoded domain frequency OCT, this is the third generation of OCT. Its functioning is identical to that of the SD-OCT, with the exception that the source light is sweeping laser light with an adjustable frequency. This light changes form to detect the various layers of retina and reflects waveforms that undergo Fourier transformation and are gathered by the photodetector. This operates quickly—roughly 400000 axial scans per second—because it makes use of a laser source.

III. DISORDERS OF THE RETINA

A. Macular Degeneration Related to Age

The macular, which is a component of the retina—the light-sensitive tissue at the rear of the human eye—is impacted by age-related macular degeneration (AMD), an eye condition that can cause central vision impairment. The eye experiences certain alterations with age, leading to the development of yellow deposits known as drusen that can range in size from tiny to big. This type of retinal illness is typically prevalent in senior persons who are 50 or 60 years of age [8][9]. Although it may not result in blindness, it can make an individual struggle to manage everyday tasks. This may be brought on by a diet heavy in saturated fats, high blood pressure, obesity, smoking, and a family history of Alzheimer's disease. The progressive dimension of vision, frequent complaints of distorted vision, and rapid, painless loss of sight in cases of neovascular AMD are all signs of age-related macular degeneration. The signs include drusen, pigmented abnormalities, and ancillary tests and slit-lamp biomicroscopy can be used to make a diagnosis based on these signs.

B. Cataract

A cataract is an illness which damages the lens in the eye. Generally speaking, this is brought on by an issue with the opacity of the lens within the capsule, which results in the development of transparent lens fiber or a degenerative process of the lens. Most cases of cataract afflict those over 50. The majority of these cataracts begin gradually and do not affect vision, but when they worsen over time, they may cause vision impairment. The symptoms of cataracts might vary depending on the kind. For example, age-related cataracts may only cause the

lens to become opaque, but other typical symptoms of cataracts include obscured or impaired vision. A doctor would often first ask about the patient's medical history and symptoms before ordering various eye tests, such as refraction or retinoscopy, visual acuity, slit-lamp examination, test for iris shadow, and distant direct ophthalmoscopic examination

C.Glaucoma

A collection of conditions collectively known as glaucoma cause gradual damage to the optic nerve, which can eventually result in visual loss. One of the key elements that causes of glaucoma. It is brought on by blocked trabecular meshwork, which in turn causes irregularities in the eye drainage system or the generation of extra fluid that accumulates in the vitreous chamber of the eye. In the early stages, this normally has no preceding symptoms that are clearly obvious, but as the intensity grows, symptoms including severe headache, eye discomfort, nausea, or vomiting, blurred vision, halos surrounding light, and redness in the eyes become noticeable. Uneven blind areas in the vision. The usual course of treatment for this is to lower internal pressure in order to stop future vision loss. Among the therapeutic options were filtration surgery, laser beculoplasty, and pharmaceutical treatment Argonordiodide.

IV. DEEPLARNING

Recently Deep learning has replaced traditional machine learning algorithms due to its automatic learning of parameters from the input, it belongs to a broad family of machine learning and Artificial Intelligence. It uses a complex algorithm called Neural networks that works similarly to the working of the neurons in the human brain. They contain input nodes that bring the data into the model, and this data is added with some weight and sent to the transfer function to give the desired output. Some of the popular deep learning models are Convolution Neural Networks, Recurrent Networks, and Autoencoders. Some of the Deep Learning techniques along with recent works in image classification of retinal diseases are discussed.

a) Convolutional Neural Network:

CNN are supervised learning techniques that are primarily utilized in the field of image processing and image. Since deep learning automatically learns parameters from the input, it has lately replaced typical machine learning algorithms. Deep learning is a member of a wide group ML and AI. It uses an advanced algorithm called neural networks, which performs activities comparable to those of a neuron in the human brain. Data is fed into the model by its input nodes, and the transfer function uses this data together with some weight to generate the desired output. Among the popular deep learning models are convolution neural networks, auto encoders, and recurrent networks. A brief overview of a few methods used in Deep Learning and ongoing work on image classification for retinal illnesses is given below. Traditional Models: In contrast to the conventional method of using convolution neural networks, there are more hidden layers, sampling methods, pre-processing techniques, parameters and neural networks in order to get a good classification accuracy. Taya et al. employed three distinct CNNs with five, seven, and nine layers in addition to some pre-processing and image enhancement methods (noise removal, edge detection, and contrast enhancement). Islam et al. sought to use two CNNs to pinpoint the areas of the picture that were impacted by the disorders. One for image classification and none for edge detection

b) Pre-Trained Models: These models have previously been trained on sizable datasets and can be applied to solve a similar type issue in the future. In these situations, the model we will develop will start with an existing model or knowledge of one, and it will require very little training to shape it in accordance with the issue description. These models can be used to deep transfer learning research being conducted now. Among the pre-trained models for image classification is VGG-16, which has three dense layers, five pooling layers, and thirteen convolution layers. Due to the increased amount of learnable factors, it operates more slowly. EfficientNet, Inceptionv3, and ResNet50. When Jing Wang et al. examined the various pre-trained models for the categorization of fundus images, it became clear that the EfficientNet not only performs better than the other models but also has the best accuracy. A comparative analysis of pre-trained models for the diagnosis of retinal disorders is presented in Table II.

c) Hybrid Models and Others:

To generate a new model for classification, multiple CNNs are combined to produce a hybrid model. To improve the image classification process, Demir , Raja along with combined two convolution models: Masked RCNN, which focuses on object detection first, and Long-Short-Term Memory (LSTM), which has a feedback connection that remembers the information from previous step or layer. Other learning strategies include the ensemble approach employed by Rastimeal, which generates a final classification with a higher confidence value by combining the output from four CNN. Karthiyayini et al. used association rule mining to classify the picture based on relationships and analyze the frequently recurring patterns. Table III presents a comparative comparison of hybrid models and other learning approaches. In addition to looking for retinal illnesses, La Cruz . likewise collected self-reports from individuals in the the NHANES who were 40 years of age or older. This led to the discovery that around 5.6% of individuals had two or more eye conditions. A few personal information and LS7 components are included in the survey. This trial demonstrated that those with good cardiovascular health had a lower risk of developing any eye diseases

TABLE I TRADITIONAL MODELS

Author	Database	Imaging	Target Disease	Architecture	Performance	Challenges
Tayal	Public dataset	OCT Scans	DME, Drusen, and CNV	CNN(5,7 and 9 layers)	Accuracy:0.965 Sensitivity:0.960 Specificities:0.986	The dataset is derived from a single demographic domain.
Islam	ODIR-5K	Fundus Image	Diabetes, AMD, Glaucoma, myopia, Cataract, and Hypertension	Deep Convolutional Neural Network	F-score:85% Kappascore:31% AUC:80.5%	A portion of the dataset's labeling is related to image quality, not to illnesses that cause input layer inconvenience.
Alqudah	Public datasets (Zhang Lab at the University of California at San Diego (UCSD) and Farsi Ophthalmology 2013 AMD dataset)	SD-OCT Scans	Age-related Macular Degeneration (AMD), Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME) and Drusen	Convolutional Neural Network	Accuracy:95.30%	The training ROC curve displays decent results, but the validation ROC curve reveals a greater true positive rate. This can be the result of sampling during the data collection.

TABLE II PRE-TRAINED MODELS

Author	Database	Imaging	TargetDisease	Architecture	Performance	Challenges
Luo	OIA-ODIR	Fundus Image	Cataract, Glaucoma and AMD	CNN (EfficientNet-B3)	Accuracy:91.43%	An increase in noise was induced by augmentation with enhancement.
JingWang.	ODIR-2019(PekingUniversityInternationalCompetition on OcularDisease Intelligent Recognition)	Fundus Image	Diabetic,Glaucoma,Cataract,AMD,Hypertension,Myopia	CNN(EfficientNet)	Precision: 0.63, Accuracy: 0.89, Recall: 0.58, AUC: 0.73, Kappa: 0.49	The model's learnt characteristics are unknown, and the amount of data on a few illnesses is minimal.
Diaz-Pinto	Public dataset(ACRIMA)	Fundus image	Glaucoma	ConvolutionalNeuralNetwork(ImageNet-trained)	AUC: 0.7678 Specificity: 0.7020 Accuracy: 0.7021 Sensitivity: 0.6893	On a different dataset, the suggested model performed badly, indicating that it was overfitted..
Syarifah	Kaggledataset	FundusImage	Cataract	ConvolutionalNeuralNetwork(AlexNet)	Accuracy:97.50%	Small data set is considered
Paradisa	DatasetforDiabeticRetinopathy(DDR)dataset from hospitalsinChina (2016-2018)	Fundus Image	Twotypes of Diabetic Retinopathy	DenseNet121and Inception-ResNetV2	F1-score: 90% Accuracy: 91% Precision: 91% Recall: 91%	The model is unable to identify the various stages of diabetic retinopathy.
Buttetal.	AsiaPacificTele-OphthalmologySociety(APTOS) dataset	Fundus Image	Diabetic Retinopathy	GoogleNet and ResNet-18	Accuracy:97.80%	Fundus image is Considered as input without artifact and noise removal.

TABLE III. HYBRID MODELS AND OTHER

Author	Database	Imaging	Target Disease	Architecture	Performance	Challenges
Demir	ODIR dataset	Fundus image	AMD, Diabetes, Glaucoma, Hypertension, Pathological Myopia, and Cataract	Region-based convolutional neural networks, Long short-term memory (R-CNN + LSTM)	Accuracy: 89.54 AUC: 97.00 F-Score: 89.97	This model to function correctly, reliable hardware is required.
H.Raja	Public dataset from Armed Forces Institute of Ophthalmology (AFIO)	OCT Scans	Glaucoma	Hybrid Convolution Network (improved version of RAG-Net)	F1-score: 0.9577 Mean dice coefficient score: 0.8697 Accuracy: 0.9117	The contextually aware component has been released recently hasn't been well tested for many different pathologies
Karthiayini et al.	Primary dataset from the medical diagnosis eye clinic, Feizhospital, Isfahan University	Fundus Image	Glaucoma, Diabetic Retinopathy	Enhanced Association Rule Mining Algorithm in Medical Analysis (EARMAM)	Accuracy: 89 Sensitivity: 93.33 Specificity: 88	Prior to transferring the data to the next stage, ROI marked regions still had noise that needed to be removed.
Cen.	Primary data: PACS, JSIEC in China, LEDRS in China, Eye PACS in the US External multi-hospital dataset: Fujian, Tibet, Xinjiang Public dataset: Messidor-2, Tele-reading	Color Fundus Image	39 fundal diseases	Two-level hierarchical system (CNN + Mask-RCNN)	F1-Score: 0.923 Sensitivity: 0.978 Specificity: 0.996 AUC: 0.9984	It is difficult to identify lesion area scan and the detection of DR1 is restricted. They employ a single eye inspection imaging
Guo	Real-time dataset	Fundus Image	Cataract	Multi-class discriminant analysis algorithm	Correct classification rate: 89.3%	The model's performance is affected by the variations in picture quality obtained from different sources.

Rasti	NoorEyeHospital,publicly available dataset (DukeUniversity, HarvardUniversity,andtheUniversity of Michigan)	SD-OCT Scans	Age-relatedMacular Degeneration	Multiscale convolutional mixture of expert (MCME)ensemble model	Precision:98.86% AUC:0.9985	The dataset that is used to train the model is small (193 retinal OCTScans).
Upadhyay	Kaggledataset	OCT Scans	Neovascularization(CNV), Diabetic Maculae edema(DME),andDrusen	Modified VGGNet	Accuracy:97.16%	The model's performance declines if The picture is not the perfect 64x64 size.

V. CONCLUSION

This review discusses the many studies conducted on the use of retinal imaging and deep learning for the detection of eye disorders.It is evident that Traditional Models outperform Pre-trained and Hybrid Models, and that taking the loss function into account might help minimize error.Additionally, it has been noted that all diagnoses of retinal disorders are dependent on a single form of imaging; however, certain diseases may be identified using a different sort of imaging, and in contrast, Limited Adaptive Histogram Equalization (CALHE) aids in the process of better picture categorization. Ineffective disease categorization may be mitigated by more study examining various imaging modalities for eye illnesses.In addition to making the models better, it's critical to educate the public about the many diseases, their causes, and their symptoms so that people can get frequent checkups and preserve their health..

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