A COMPREHENSIVE REVIEW ON DEEP LEARNING TECHNIQUES USED IN DIAGNOSING RETINAL DISEASES ON FUNDUS IMAGES

Abstract

Due to the exponential growth of the computing infrastructure, there has been an unheard increase in the deployment of computer vision, deep learning in recent years. This was true for fundus image processing: effective AI models were created employing a range of visual markers extracted from eye image data to identify various retinal diseases. The detection of five important eye diseases—diabetic retinopathy, glaucoma, age-related macular degeneration, cataract, and retinopathy of prematurity—has been made possible in recent years by the use of a variety of deep learning techniques. This article is structured along a pipeline for implementing deep learning, providing a detailed overview of different approaches to each of the five aforementioned retinal diseases, followed by an introduction to commonly used datasets, metrics, image preprocessing techniques, and basic models for deep learning. The article concludes by listing the eight main study areas that are now being studied in the area of diagnosing retinal diseases, outlining their primary difficulties and potential future prospects for the research community at large.

Keywords : Glaucoma • Retinal Fundus Images •Computer Vision • Deep Learning •Detection• Medical Image Analysis

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I. INTRODUCTION

Numerous imaging modalities have been developed over the years to examine the human eye, but fundus imaging is becoming more popular due to its non-invasive and inexpensive properties. In fundus photography, a monocular camera is used to record the fundus or its projection onto a two-dimensional plane. 2D fundus scans can be used to identify various ocular structures, biomarkers, and abnormalities (Figure 1). Identification of retinal disease is greatly facilitated by many of these visual indicators. Micro aneurysms (MAs), which resemble small red dots, usually develop as a result of narrowing of capillaries and lack of oxygen. A complete loss of supply due to certain arteriolar occlusions (SE) results in soft white patches called ointments. If a retinal artery ruptures due to pressure build-up within the arteriole, it may bleed and appear as a dark red spot. Hard exudate (HE), a hard, yellow, waxy substance, results from protein and fat leaking out of defective blood vessel walls. We investigate the presence of these lesions in combination with other retinal biomarkers. B. The macula, fovea, optic disc, and blood vessels provide important insights and help in diagnosis of some of the most important retinal diseases.

In the densely populated countries for example India, it is a serious shortage of qualified eye specialists capable of such a tedious task [1].

The common eye diseases that leads to blindness not properly treated include diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD) and diabetic macular edema (DME), retinopathy of prematurity (ROP) and cataracts. Such retinal diseases usually require specialist care and comprehensive screening techniques [2].

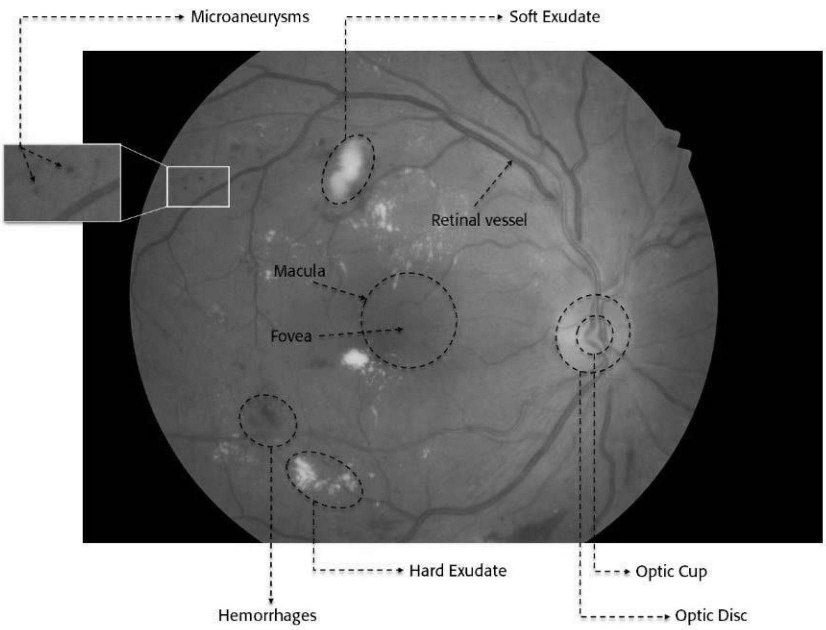

Figure1: Fundus Image

Classification, segmentation tasks are the two main types of DL tasks used in the diagnosis of retinal diseases. The task of direct classification of input photos into multiple illness categories is referred to as the classification task. Similar to this, segmenting is important for biomarkers and significant lesions from a patient's fundus image can offer a wealth of information on the nature and classification of retinal illnesses. For such purposes, numerous DL architectures have been created and evaluated, as is extensively illustrated in [3].

Digital processors have grown exponentially recently, data-driven technologies have made AI-based medical screening systems increasingly common. These systems provide workable and affordable options for the automatic identification of retinal illnesses. In particular, fundus image analysis has shown tremendous growth and promise in computer vision, deep learning techniques. [4].

In addition, this article uses a DL process pipeline approach to diagnose retinal diseases and provides a summary of current research on the five main eye illnesses that can be diagnosed. Retinopathy of prematurity, diabetic retinopathy, glaucoma, age-related macular degeneration, and cataract. This contrasts with newly released reviews [5] through [9] on the same topic.

In addition, it fully describes all datasets that are available for the aforementioned illnesses together with ground truth descriptions.

It includes an extensive literature review of DL implementations for five major retinal diseases and tabulates their comparative performance. In addition, we discuss the various research directions currently available in this field. We provide knowledge about widely used image pre-processing methods, evaluation methods, and commonly used DL backbone approaches for the diagnosis of retinal diseases.

II. DATASETS AND EVALUATION METRICS

Fundus photography a method of acquiring a three-dimensional fundus image of the retina in two dimensions using reflected light projected onto the image plane. Commonly used fundus image dataset for DL-based diagnosis of retinal diseases. The dataset is used for disease diagnosis and the results are color coded. All records are presented in one table for ease of understanding and comparative analysis.

III. PREPROCESSING TECHNIQUES

Fundus images are typically pre-processed before training to enhance learning and create meaningful predictive models. A learning step is performed to compensate for noise caused by different types of imaging devices used with different lighting settings during image capture. As shown in Figure 2, many important biomarkers and lesions may go undetected due to the complexity of the retinal structure and poor image quality. Pre-processing techniques are mainly enhancing the features of the fundus image and remove unwanted noise before running the DL model. Table 2 lists some of the commonly used pre-processing methods for diagnosing retinal disease from color fundus images.

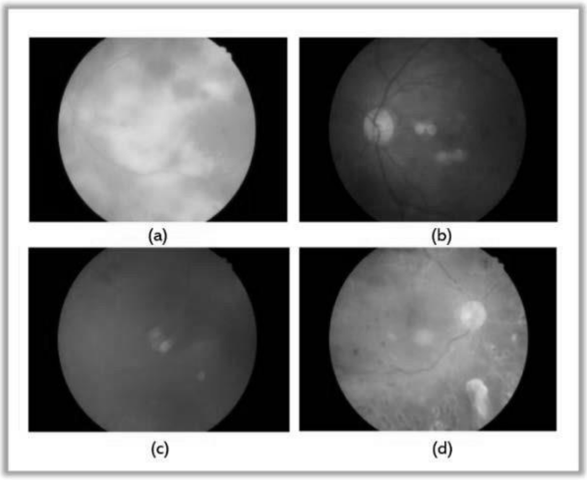

Figure 2:- Retinal Fundus Images

Fundus Preprocessing Technique	Explanation
CLAHE(Contrast Enhancement)	CLAHE is a widely used technique especially in fundus images.
Color Space Transformation	Green channel extraction from fundus Images are well known for providing high-contrast images.
Noise Removal	Many denoising expressions such as Gaussian filter, median filter and non- local means denoising are used to remove unwanted noise.
Cropping and Extracting ROI	To extract a specific region of interest from the whole fundus picture, cropping is used. For instance, only this area of the image is cut and utilized as a ROI for model training in order to examine the size of the optic disc, hence eliminating needless learning effort.
Augmentation	Augmenting approaches such as image rotations, rescaling, mirroring and transformation are used to balance the image dataset.

Table 2: Commonly used Preprocessing techniques for Image Enhancemen

IV. DEEP LEARNING TECHNIQUES

Deep learning (DL), based on artificial neural networks, is a subclass of artificial intelligence techniques (learning methods inspired by the biological structure of the human brain). Potential and intrinsic relationships of input data are automatically learned through the mathematical representation of the DL process. Unlike common machine learning (ML) techniques, deep learning (DL) techniques extract meaningful features directly from data without relying on manually created features. This makes DL eligible for medical image analysis because it can automatically learn features from complex visual data. In this section, we describe the design of several commonly used basic models, especially for classification and segmentation tasks in the diagnosis of retinal diseases.

V. MODELS OF CLASSIFICATION

1. **Convolutional Neural Networks (CNN):** CNN (Convolution Neural Network) architecture is one of the most commonly used DL designs for effective multi-layer training [10]. The overall structure of CNN is shown in Figure 3. A CNN consists of three main parts. Convolutional layers, pooling layers, fully connected layers. The training process consists of two steps. The first stage is called the "forward stage", where the input image is rendered with the correct weights and distortions at each level. The expected output is then used to compute the loss function by comparing it to the ground truth values. His second stage, called the "backward stage", uses a loss function to compute the gradient of each parameter. Parameters are set and changed for subsequent transfers.

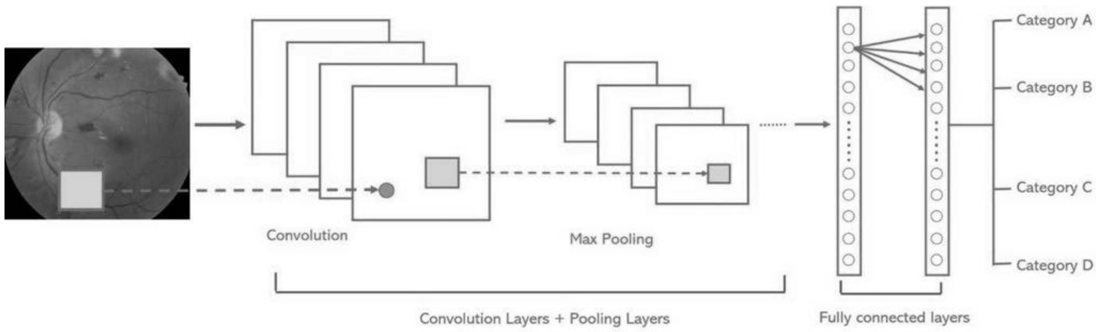

Figure 3: CNN Architecture

2. **VGGNET:** VGG Network is yet another backbone network that is frequently utilized to classify retinal disorders (VGGNet). In 2014 [11], Karen Simony and Andrew Zisserman made this suggestion. The architecture of a VGGNet is seen in Figure 4. The VGG acronym stands for VGG, which starting with VGG-16 through VGG-19 produced numerous versions of Convolution network for the several of image categorization techniques. Researching the depth of CNN affects the precision of picture classification was the initial motivation for the creation of VGG. In order to improve the depth of network without using so many parameters, a tiny kernel is employed in all levels of the model.

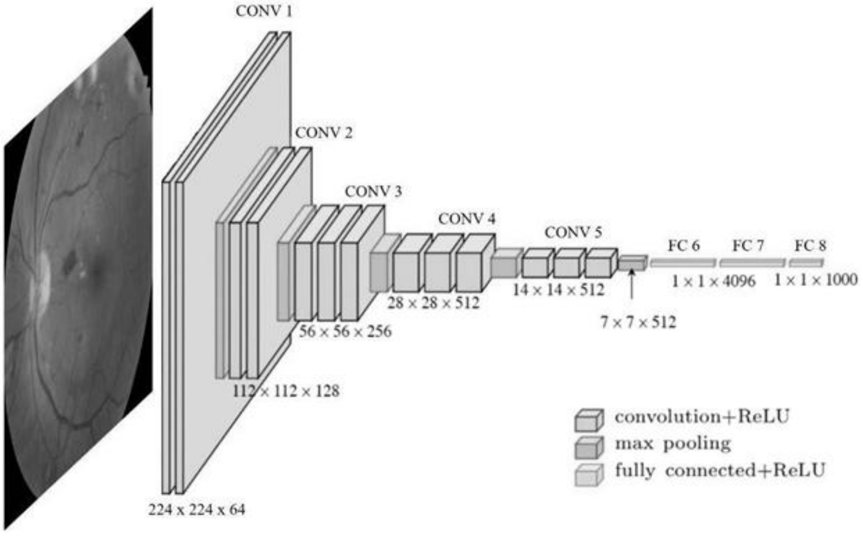

Figure 4: VGGNET

3. **RESNET:** The 152 layers that make up the residual network (ResNet) [12] are created by stacking individual residual blocks shown in Fig. 5(a) and (b). These residual blocks consist of two convolutional layers (3 3). The number of filters that doubled periodically and a step size of 2 is used for spatial down sampling. After each convolutional layer, this network uses stack normalization and specific hopping connections. These deep models take activations from one layer that pass them directly to another layer, so hop connections are used to optimize them. As a result, the vanishing gradient problem is avoided during deep network training. To cut down on the amount of parameters, ResNet features a fully connected layer that outputs 1000 classes.

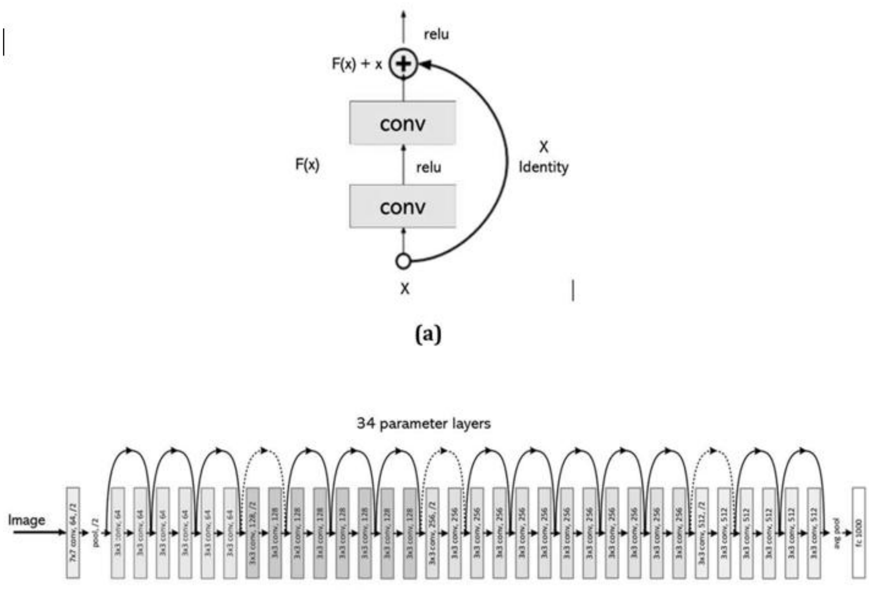

Figure 5: a) Residual Block b) Architecture of ResNet

4. Backbone Models of Segmentation In Fundus

- **Fully Convolution Networks (FCNs):** A modified CNN network was proposed by Long et al. [13] by substituting up sampling layers for fully linked layers (Figure 6). The initial layers' extracted features are up-sampled to the input image's size. In comparison to CNN, a fully convolution network is more suitable for segmentation tasks because to its ability to execute dense pixel-wise prediction.

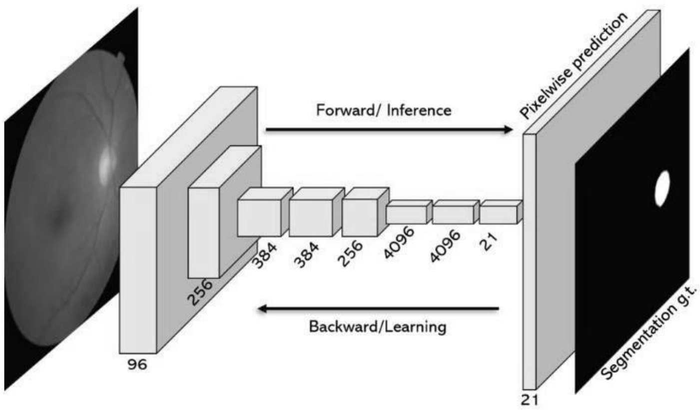

Figure 6: FCN Architecture

- **U-NET:** Ronneberger et al. suggested a network with multiple-hop links from the encoding path to the decoding path, as well as symmetrical encoder and decoder topologies. Presented, as seen in Fig. 7 and [14]. While the decoder reconstructs the image for the final output, the encoder is in charge of extracting features from the input image. Hop arrangement allows the network to directly link low- level feature maps from the encoder to the decoder, improving predictions.

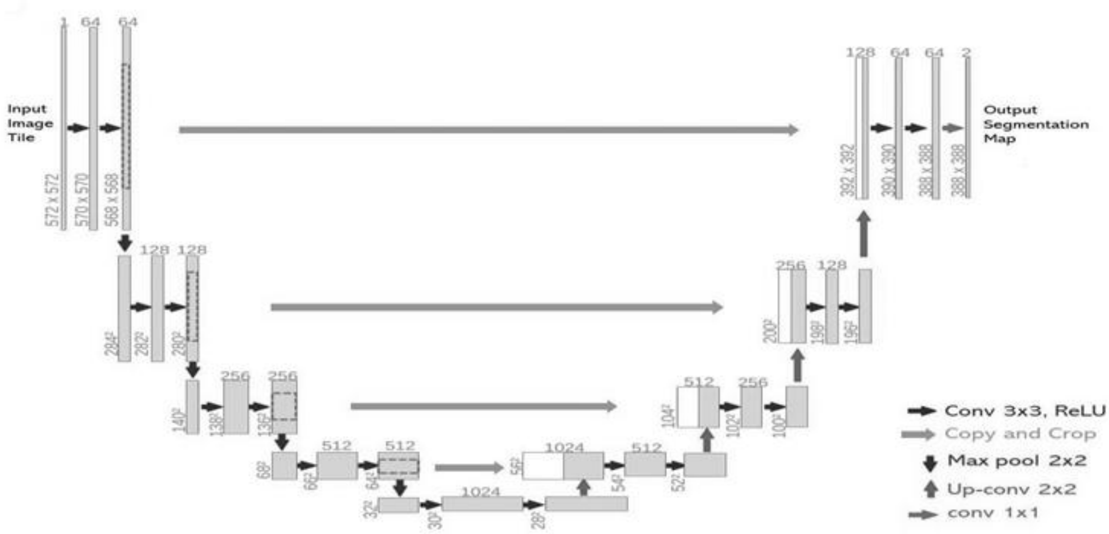

Figure 7: U-Net Architecture

VI. DEEP LEARNING RETINAL DISEASE DIAGNOSIS PROCESS

1. **Diagnosis Diabetic Retinopathy:** One of the most common retinal diseases that lead to blindness is diabetic retinopathy. One-third of diabetics suffer from this problem [15]. According to research, around 93 million people worldwide are affected by DR [16]. Any person with diabetes can get DR, which leads to the destruction of retinal blood vessels. These numbers are expected to increase further, given the rapidly increasing number of people with diabetes worldwide [17]. The International Clinical Diabetic Retinopathy Scale (ICDRS), which rates the severity of DR, divides it into five classes: Class 0 for no DR, Class 1 for mild DR, Class 2 for moderate DR, Class 3 for severe DR and Class 4 for proliferative DR. In order to generate a trustworthy DR diagnostic model from fundus pictures, numerous DL models have been implemented.

2. **Glaucoma Diagnosis:** Another important factor contributing to permanent blindness worldwide is glaucoma [18]. The researchers are focused on creating multiple DL models for diagnosing glaucoma from fundus images, as they have done for many other retinal diseases. The following section describes recent progress in this direction. By extracting OD, OC and also retinal nerve fiber layer (RNFL) features, Xu et al. [19] created a DL framework for diagnosing glaucoma using a relatively less number of training snippets. Pre-diagnostic classification is based on common fundus images (global attributes) in frames. In the next step, segmentation of the above biomarkers is performed with ISNT and MCDR values calculated. All segmentation data were used to perform final diagnostics. The cup-to-disk ratio (CDR) was determined by Shanmugam et al. already used. [20] Detect glaucoma on fundus images. Their approach is mainly focus on the values of accurate segmentation of OC and OD performed via improved U-Net. By incorporating adaptive convolution into the framework, we use fewer filters and less computational effort than traditional U-Net. Glaucoma images were separated from healthy fundus images using a random forest classifier using attributes obtained from segmentation values. In a different study, Wang et al. [21] trained a model and classified glaucoma using VGG-16 and Alex Net utilizing a transfer learning technique. From several accessible sources, they built two collections of ONH images. Several data augmentation approaches have been used to enhance the dataset. B. Random cropping, rotation, flipping, and scaling.

   Nayak et al. [22] developed a network using a biological phenomenon-based trait optimization technique, the so-called real-coding genetic algorithm, to overcome problems such as over fitting and the need for large datasets (RCGA). After the improved features are obtained using this method, different classifiers are used to identify glaucoma-based images. I got the best results when using the RCGA algorithm and his SVM classifier. To test and train the model, see Li et al. [23] developed CNN architecture with 101 layers and 26,585 images. By implementing frisk connection in the middle of layers throughout the training phase, we were able to avoid the vanishing gradient problem. A CNN-based technique was developed by Hemelings et al. developed. [24], combined active his learning techniques and transfer learning for accurate diagnosis of glaucoma. According to Juneja et al. [25], the images were mapped to a CNN-based model after undergoing specific preprocessing methods such as image cropping, enlargement and denoising (76 layers deep). They used an "additional layer" in each block that combined the previous block's output with the next block's output to compensate for the missing data. A glaucoma diagnostic pipeline that can be used offline on mobile devices has been published by Martins Et al. Created. [26]. they mainly used his U-shaped model (OD and OC segmentation) to generate favorable morphological features that are exploited by another classification network (He based on MobileNet-V2 as backbone). Glaucoma classification was adapted from Bajwa et al. carried out. [27] In two steps. Region using CNN (RCNN) is used in the initial stages of OD extraction and localization. It also features a semi- automatic ground truth generation component to generate ground truth including OD positions for training RCNN. The second stage uses the ROI image (created after OD extraction) for classification and consists of 4 convolutional layers and 3 fully connected layers. A network of two tasks was developed by Kim et al. I suggested. [28] Utilizing different CNNs for glaucoma classification and "gradient-weighted class activation mapping" to pinpoint the glaucoma regions of a specific fundus image that are the most suspect. Among the different CNN variations, the ResNet 152-M model produced the most encouraging results.

Glaucoma classification by Bajwa et al. [29] It was split into two sections. OD extraction and localization are carried out utilizing "Regions using CNN" (RCNN) in an initial step. Additionally, it has a semi-automatic ground truth generation component that uses OD locations to create ground truth while training RCNNs. The second stage employs his ROI pictures (produced after OD extraction) and four convolutional layers and three fully connected layers for classification. According to a two-task network described by Kim et al. [30], the most likely glaucoma regions inside a given fundus image can be found by using "gradient-weighted class activation mapping" in conjunction with several CNNs for glaucoma classification. The ResNet 152-M model showed the best results across the several CNN iterations.

A 201-layer dense network was reported by his Ovreiu et al. I suggested. [31] To improve performance of glaucoma categorization. Layers in the network are built on the input of the previous layer. In another study, Saravanan et al. [32] presented auto encoder architecture for diagnosing glaucoma and AVP decrement. They paid special attention to reducing classification errors by implementing multimodal learning. The effectiveness of his three pre-trained CNN-based models detecting glaucoma at early stage reviewed by Shoukat et al. compared. [33]. The RIM-ONE, G1020, REFUGE datasets were used to run the tests. For the G1020 dataset, pertained EfficientNet- B7 gave the best results. Islam et al. used a private dataset of 643 fundus photographs to study. [34] Performance of various DL models such as DenseNet, Mobile Net, EfficientNet and GoogleNet. Ovreiu et al. [31], he suggested a 201-layer dense network to improve the effectiveness of glaucoma classification. Inputs from previous layers are used to build the layers of this network. In the other study, Saravanan et al. [32] illustrated auto encoder architecture to diagnose glaucoma and his AVP identification. They focused especially on combining multimodal learning to lower categorization errors. The efficacy of Shukat's three pre-trained CNN-based models for glaucoma early detection was investigated by Shukat et al. [33]. The RIM-ONE, G1020, and REFUGE datasets were tested with. The pre-trained EfficientNet-B7 showed the best performance on the G1020 dataset. The performance of techniques by various authors is defined in Table [3].

References	Dataset	ACC	SE	SP	AUC	F1
[19]	Private-Tongren		0.961	0.939	0.981	
[20]	DRIONS-DB,HRF	0.943	0.907	0.979	0.991	
[21]	Private		0.940	0.860		
[22]	Private-Kasthurba Medical College, Manipal	0.980	0.974	0.988		0.983
[23]	Private	0.953	0.96	0.939	0.944	
[24]	Private		0.980	0.910	0.995	
[25]	DRISHTI-GS,RIM-ONE	0.870	0.85		0.93	
[26]	Origa,Drishti,iChalenge, RIM- ONE,RIGA	0.870	0.85		0.93	
[27]	ORIGA,HRF,OCF&CFI		0.717		0.874	
[28]	SamsungMedical Centre,Soeul	0.96	0.95		0.99	0.97
[33]	G1020	0.992	0.98	0.97		
[34]	G1020	0.98	0.951	0.94		

Table 3: Glaucoma Diagnosis Performance Comparison

3. **OC/OD Segmentation:** Optic disc (OD) and optic disc are two other important retinal indices used to diagnose glaucoma (OC). The vertical cup and disk diameter are mainly used for calculating the cup-to-disk ratio. Therefore, correct OD/OC segmentation is essential for diagnosing glaucoma diagnosis and much work is done. In addition to experimental results, his recent work on DL-based Optic and Optic Cup segmentation will be discussed in future.

4. **AMD Diagnosis:** The main causes of blindness in most of the senior people are age-related macular degeneration (AMD) [35]. AMD typically damages the retina's macular area. According to a study, there would be 288 million AMD sufferers worldwide by the year 2040, up from an estimated 196 million people in 2020 [36]. In the section that follows, we go over various DL-

based approaches used recently for automatic diagnosis of AMD. In order to distinguish between neovascular AMD (NAMD) and (PCV), Chou et al. [37] combined an image-based Deep Learning technique with biomarkers obtained from OCT using a stacking technique. Multiple Correspondence Analysis (MCA), a brand-new technique, was developed to transform OCT biomarkers into continuous main components. Fundus pictures were trained and validated using EfficientNet-B3. For precise predictions on new input photos, the ensemble stacking technique produces the optimal combination from the aforementioned two paths. Yan et al. [38] developed a method employing a modified Deep CNN to forecast the evolution of late AMD. Their model takes genotypes into account in addition to fundus photos for increased accuracy. In order to distinguish between neovascular AMD (NAMD) and polypoidal choroidal vasculopathy (PCV), Chou et al. [37] integrated a fundus image-based DL model with biomarkers obtained from optical coherence tomography (OCT). Using a cutting-edge method called Multiple Correspondence Analysis (MCA), OCT biomarkers were transformed into continuous main components. Fundus pictures were trained and validated using EfficientNet-B3. The ensemble stacking method creates the ideal mix from the aforementioned two approaches to exact predictions on new input images. Using a modified Deep CNN, Yan et al. [38] designed a methodology for forecasting the evolution of late AMD. Their model takes genotypes into account in addition to fundus photos to increase accuracy.

To classify AMD and PCV, Xu et al. [39] designed a dual-deep CNN using two of kind fundus, OCT images. To take advantage of transfer learning, weights from ResNet-50 were first applied to two independent models taking inputs separately from fundus and OCT images. The weights were refined with new data and then transferred to the appropriate convolutional block. Finally, FC layer is created to classify input values into Wet AMD, Dry AMD, PCV, and AMD categories. The other study based on segmentation for AMD detection was published by Pham et al. Published. [40] Attempted to address the problem of data unevenness, as the number of non-druze values was significantly higher than the number of dreuze pixels. Use of images in various modalities.

Xu et al. [39] developed a dual-deep type CNN model to classify AMD, PCV using two of kind fundus, OCT images. Weights from ResNet-50 were first applied to two different models containing inputs from fundus and OCT images separately to take advantage of transfer learning. The weights were refined using new inputs and assigned to the appropriate convolutional blocks. Finally, the input pairs were classified into Wet AMD, Dry AMD, PCV, and NAMD categories and FC layers were constructed. Pham et al. [40] published another study using drusen segmentation for AMD detection.

5. **Cataract Diagnosis:** If a retinal disease is identified and treated promptly, cataract is one of a major retinal disease, can cause irreversible vision loss [41]. According to a recent study, cataracts are responsible for roughly 33.6 million cases of blindness, or 45% of all occurrences of blindness worldwide [42]. There have recently been numerous attempts for detecting cataract on fundus images. Below is a discussion of recent advancements in this area and a comparison of the performance of several DL models.

The activation and loss functions for CNN-based architectures are published by Junayed et al. Changed. [43] Reduce training values and computational load when priming a model for detecting cataract. Additionally, he evaluated the recognition accuracy of the three alternative models using 3, 4, or 5 CNN blocks, depending on the model. The 4-block model gave the best results without over fitting. By combining CNN and recurrent neural networks, Imran et al. [44] Suggested a cataract classification model (severe, moderate, mild, normal) (RNN). After preprocessing, the dataset's fundus images were separated into 12 patches. Then, 12 pretrained CNN models (GoogleNet, AlexNet, VGGNet, and ResNet) processed each patch to extract features.

6. **ROP Diagnosis:** Infants' fundus vasculature is most impacted by the retinal illness known as retinal retinopathy of prematurity (ROP). Children who have this illness may experience serious outcomes like retinal detachment and total blindness due to neo-vascularization. Identification of an early symptom known as well as disease-causing abnormalities to preterm infants' retinal blood values is crucial for prompt treatment Ramachandran et al. developed a framework to detect an infant's ROP by detecting additional diseases from fundus images. [45]. this network, in a semi-supervised approach, creates boxes values around unhealthy vessels that identifies presence of disease in retinal images by the number of these frames. This is accomplished by using a convolutional neural network to detect twisted vessels affected by the YOLO architecture. This model is first trained using the manually labeled fundus images to create bounding box images (pseudo-labeled images) and they are retrained using the human labeled images and pseudo-labeled images. The model is then used for ROP prediction. Establish a system of ROP diagnosis and supported medical follow-up care.

VII. RESEARCH DIRECTIONS

It was covered in the previous sections, testing and assessing different network topologies for the diagnosis of retinal diseases has advanced impressively using DL approaches. Future research has a lot of potential and uncharted territory, nevertheless.

1. **Weekly supervised Learning Models:** The availability of annotated fundus photos is somewhat constrained when compared to natural image data sets like ImageNet, which has about 14 million images, despite the fact that many fundus image data sets are publically accessible. With regard to their ground truth labeling, the fundus datasets that are readily available are likewise varied. Researchers can look at weakly supervised learning models for training the original fundus images with various ground truth labels, even though other methods like image synthesis that can produce artificial fundus images are also being investigated in parallel. Weakly supervised training methods can produce robust model performance for diagnosing retinal disorders, even on incompletely or inaccurately annotated datasets.

2. **Fundus Image Fusion:** Generative adversarial networks (GANs), which have gained recent prominence, have the ability to produce artificial fundus images that can be used to supplement training datasets. Predictive performance is enhanced and the shortage of high-quality data is successfully eliminated. The synthesis of pictures for DR, glaucoma, and AMD has been shown in recent studies, but the topic is still young and has plenty visual room for additional study.

3. **Light Weight Network Design:** Most of the Deep Learning models are created for diagnosing fundus diseases works fine but use up a lot of computational resources. Implementing these models on the portable edge devices faces this significant obstacle. The creation of new, lightweight models to cut down on computing requirements while retaining performance is another open research area in this area.

4. **Improving Generalization:** We found that the performance of the DL models varies due to different image acquisition settings for each dataset, with certain models succeeding on some datasets while failing on others. By exploring alternative domain matching approaches, researchers can focus on improving the model's performance for generalization. The underlying goal of these methods is to reduce the distribution gap between the source and target data domains. Existing reconciliation techniques include moment matching, which minimizes distribution differences at the feature level, and different learning, which reconciles source and also the target domains. Consider the difficulty of creating retinal fundus images, the field of domain matching offers many potential opportunities for researchers to improve model generalization.

5. **Implementing Federated Learning:** Most hospitals and other research institutions are reluctant to share fundus photographs with others due to various privacy restrictions. By limiting model training to just publicly accessible datasets and making training on the vast and varied private fundus data available in hospitals unavailable, this further exacerbates the problem of data scarcity. You can use methods like federated learning to locally train models with confidential data. The global model is updated with the learned weights.

6. **Diagnosing Multiple Diseases:** Simultaneous detection of many retinal diseases by DL is another interesting research area. Helps doctors identify patients with multiple retinal diseases. In this area, studies such as "simultaneous diagnosis of DME and DR" and "simultaneous diagnosis of AMD, DR and glaucoma" have already been conducted, but research has not progressed sufficiently.

7. **Smart phone based Retinal Disease Diagnosis:** The most recent research field uses retinal images obtained by big-resolution fundus examinations. Researchers have plenty of room to create models which are used to learn from fundus photographs taken with phones. This helps to establish method for remotely examining the eye.

8. **Evidence Maps:** One of the main issues with Deep Learning implementations on retinal disease detection is getting buy- in from medical experts for AI-based models. Few studies have been conducted to increase the predictability of outcomes. A solution to this problem is to create an evidence map for the prediction of Deep Learning and display or highlight the key fundus image regions that the deep network relied on for the final decision. Although certain methods have advanced in this area recently, there is still much to be learned about how to improve the quality of evidence maps. For example, since Glaucoma diagnosis relies on the detection of a large number of lesions and markers on fundus images, it is possible to provide high-quality evidence maps with accurate lesion segmentation and simultaneous Glaucoma grading.

VIII. CONCLUSION

Automated eye disease detection systems are critical due to the excessive quantity of patients and healthcare professionals. Color fundus imaging, which expresses a variety of eye-related disorders in picture format, has significantly broadened the research field in terms of medical image analysis. Automated disease diagnosis has been tried and used using a variety of DL models. We can now take a particular fundus image and extract the salient elements using sophisticated image processing techniques. Today, lesions like micro aneurysms, effusions, and bleeding can be used to diagnose illnesses at an early stage. These make up a significantly lesser portion of the fundus image's pixels. This review offered a method-based approach for comprehending cutting-edge DL methods used in the diagnosis of ocular illness.

A compilation of all publicly available image datasets is provided with truth descriptions, as the performance of the DL model is highly dependent on the training dataset. A number of databases such as IDRiD, Messidor and DRIVE have been found to provide excellent fundus photographs taken in controlled environments. For other datasets, models are trained on datasets may not perform well. On the other hand, photos taken in different environmental conditions can be found in databases such as Kaggle and Eye-PACS. These may not be effective, but simulating real-world conditions can guide the behavior of your model in useful directions. A collection of balanced datasets can be used to develop robust models for clinical use.

Most of the studies show that image preprocessing techniques such as contrast enhancement, color conversion, fundus magnification, and filtering is to be used to improve the ability of DL models to extract disease-related features during the training phase.

In a recently released study, a method for diagnosing diseases utilizing various bone models was established. Using several skeleton models, networks such Basic CNN, VGG, ResNet, and a recently published study created a method for disease diagnosis. For classification tasks, networks like Basic CNN, VGG, ResNet, and Inception are employed, whereas networks like U-Net, FCN, Mask RCNN, and Seg-Net are used for segmentation tasks. Usually, these backbone models served just as a starting point for research. To enhance model performance and offer precise diagnostics, other learning paradigms such group learning, transfer learning, multitask learning, and active learning were also investigated. One of the retinal diseases garnering the greatest clinical and research interest is diabetic retinopathy. Disease classification is only one aspect of the present core research on DR focuses on creating interpretable heat maps.

Delay in treatment for the retinal illnesses discussed in this study can result in total vision loss, making them very important. Recently, there has been a noticeable increase in interest in employing DL to diagnose retinal disorders. The DL model fared better than the pros in some instances. Given the need for DL systems to be improved further and integrated into clinical practice, the future of effective and successful patient treatment is still very uncertain.

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