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A Review on Diabetic Retinopathy Detection Methods

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Abstract: *Diabetes mellitus frequently results in diabetic retinopathy (DR), which results in lesions on the eye that impair vision. Blindness may result if it is not caught in time. Unfortunately, there is no cure for DR; treatment only preserves eyesight. Early diagnosis and treatment of DR can greatly lower the chance of vision loss. In contrast to computer-aided diagnosis methods, the manual diagnosis of DR retinal fundus images by ophthalmologists is time-, effort-, and cost-consuming as well as prone to error. Recently, deep learning has become one of the most common techniques that has improved performance in many areas, especially medical image analysis and classification. Convolutional neural networks are more frequently employed as a deep learning technique in the study of medical images, and they are very successful. In this paper, state-of-the-art techniques for deep learning-based detection and classification of DR color fundus images have been reviewed.*

Keywords: Diabetic Retinopathy, Convolutional Neural Networks.

I. INTRODUCTION

Diabetic Retinopathy (DR) is a complication of diabetes that affects the eyes. It occurs when high blood sugar levels damage the blood vessels in the retina, the light-sensitive tissue at the back of the eye that allows us to see. In the early stages of diabetic retinopathy, there may be no symptoms or only mild vision problems. However, as the condition progresses, it can lead to serious vision loss and even blindness. Some common symptoms of diabetic retinopathy include blurred or distorted vision, dark or empty spots in your field of vision, and difficulty seeing at night. Diabetic retinopathy is classified into two types:

A. Non-proliferative diabetic retinopathy (NPDR) is the early stage of the disease in which symptoms will be mild or nonexistent. In NPDR, the blood vessels in the retina are weakened. Tiny bulges in the blood vessels, called microaneurysms, may leak fluid into the retina. This leakage may lead to swelling of the macula.

B. Proliferative diabetic retinopathy (PDR) is the more advanced form of the disease. At this stage, circulation problems deprive the retina of oxygen. As a result, new, fragile blood vessels can begin to grow in the retina and into the vitreous, the gel-like fluid that fills the back of the eye. The new blood vessels may leak blood into the vitreous, clouding vision. It is essential to detect and manage diabetic retinopathy as early as possible to prevent permanent damage to the eyes. Regular eye exams are crucial for detecting diabetic retinopathy, even if you have no symptoms. Treatment options for diabetic retinopathy include medications, laser therapy, and surgery. Early detection and treatment of DR can be more cost effective than treating advanced cases that require more extensive interventions such as hospitalization or surgery.

II. LITERATURE SURVEY

In this section different methods for diabetic retinopathy detection is discussing.

A Hybrid Retinal Image Enhancement Algorithm for Diabetic Retinopathy Diagnosis Using Deep Learning was put forth by Saif Hameed Abbood and Haza Nuzly Abdull Hamed in 2022[1]. Pre-processing stages in the suggested algorithm include noise reduction, contrast enhancement, and color normalization. The enhanced retinal images are then classified into various stages of diabetic retinopathy using a deep learning model that has been trained to learn the characteristics of the images. A threshold and image are inputs to the algorithm. The threshold intensity level is used to distinguish between foreground and background. Images in RGB and grayscale are both taken into account by the algorithm. The intensity level must be greater than the threshold, according to the specifications used to construct the mask. The mask isolates the foreground in both grey and RGB images, and the segmented image is given back in the same format as the input image. The segmented images are then output after that. To enhance the image quality and

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contrast the presence of vessels (in their normal or abnormal condition), a circle crop and gaussian blur algorithm were used. The Resnet architecture serves as the foundation for the feature extraction and classification model. The categorization accuracy was 0.92 and the sensitivity was 0.82.

In the same year Aiman Hasan Mohammed Mohammed And Dr. Mesut C¸ evik proposed an application of convolutional neural network (CNN) model called GoogleNet for the classification of diabetic retinopathy[2]. To detect instances of retinal diabetes, an implementation of the CNN architecture powered by GoogleNet was developed. The grayscale images undergo Contrast-limited Adaptive Histogram Equalization (CLAHE) optimization while the colour images undergo filtering and optimization processes in order to diagnose and classify retinopathies using a convolutional neural network. Google's GoogleNet CNN design was used in this technique. While editing, the top layer is manually chosen. The first layer determines the largest possible image size. A 224x224x3 image is needed for Google Net. The images are resized to suit the specified size of the initial input layers of therelevant architectures before being supplied to the network to be trained. The RGB values are averaged across this collection of images. The average of the red, green, and blue channels is used. Each pixel's value is deducted from each channel's value. Then, these images were trained using a variety of different training conditions. Based on the findings of the comparison, the GoogleNet CNN option GoogleNet CNN option seems to be the best way to diagnose diabetic retinal disease. In 3 minutes and 11 seconds, it displays 0.96 accuracy with a good fit result.

MD. Nahiduzzaman and MD. Robiul Islam proposed a Hybrid CNN-SVD Based Prominent Feature Extraction and Selection for Grading Diabetic Retinopathy Using Extreme Learning Machine Algorithm in 2021[3]. To extract and choose standout features from retinal images, the authors combine convolutional neural networks (CNN) and singular value decomposition (SVD). The images are then classified into various categories of diabetic retinopathy using the extracted features that were fed into the extreme learning machine (ELM) algorithm. Images have been blurred using the gaussian blur method in the initial steps of pre-processing to reduce noise. The blurring process is known as Ben Graham. After applying blurring, contrast-limited adaptive histogram equalization (CLAHE) was used to improve the contrast in the image. The images are now in grayscale with a single channel following the application of Ben Graham's method to fundus images (FI).The single-channel has been copied into three channels, and CLAHE is applied to these processed pictures because CLAHE is effective with RGB images. The lessons are clearer after conducting CLAHE. In the beginning of this technique, features were extracted using CNN. Batch normalization and max-pooling layers have been added after each convolutional layer (CL) of a CNN. By re-centering and re-scaling the inputs to the layers, batch normalization boosts the model's speed and efficiency. Adam has been selected as an optimizer because it works well with large amounts of data. The characteristics have been standardized after being extracted. Lastly, dimensionality reduction has been accomplished using SVD. The method uses an ELM algorithm as the classifier, which minimizes the training time cost. The proposed model achieved an accuracy of 0.9809 and 0.9626 for the APTOS-2019 and Messidor-2 datasets, respectively.

A method called CABNet Category Attention Block for Imbalanced Diabetic Retinopathy Grading is introduced by Along He, Tao Li and Ning Li, Kai Wang in 2021 to address the issue of imbalanced data in the grading of diabetic retinopathy[4]. The authors' model includes the CAB attention mechanism and a deep convolutional neural network (CNN) design. The CAB mechanism seeks to improve the classification accuracy for the minority classes by selectively focusing on the features that are important for each category of diabetic retinopathy. The backbone network serves as a feature extractor for CABNet, which uses it to create the global feature maps from an input fundus picture. Adopted a CNN pre-trained on ImageNet as the backbone network to extract feature maps from the last convolutional layer, which contain high-level semantic features of fundus images. Applying an 1×1 convolutional layer helped to lower the memory and computational costs. The Global Attention Block (GAB), which has a single-branch structure, comprises of channel attention and spatial attention. By learning the channel-wise attention weights, which represent the relative significance of each feature channel and are used to suppress less informative channels, it serves as a feature selector for channel attention. Through the learning of spatial attention weights, which are an addition to channel attention, spatial attention highlights the significance of each spatial location. In order to improve the fine-grained DR grading task, Category Attention Block (CAB) is developed to learn the discriminative regions from fundus images. Each DR category is given equal consideration as the CAB learns to pay attention in a category-by-category way. It guarantees that each DR grade has an equal number of feature channels and allots a specific number of feature channels to each

DR category, helping to prevent channel bias and widen the gap between various DR categories. As a result, CAB can successfully address the issue of uneven data distribution that pervades DR rating datasets. For each DR category, CAB mines more discriminative regions than other CNNs, reducing feature duplication and setting it apart from other global attention blocks like channel attention and spatial attention. In order to emphasize more precise and instructive regions for DR grading, the CAB learns discriminative regions linked to lesion information. The accuracy of this technique was 0.931.

In 2021 Ziyi Shen and Huazhu Fu proposed a method for enhancing low-quality retinal fundus images using a clinically oriented fundus enhancement network (cofe-Net) model [5]. The images must be corrected while ensuring that they continue to be clinically relevant for disease detection and analysis. To fix the poor fundus picture, a clinically focused fundus enhancement network (cofe-Net) was suggested. The retinal artifacts are recognized using a low-quality activation (LQA) algorithm. The convolutional encoder-decoder architecture serves as the foundation for the LQA module, which creates an artifact attention map corresponding to the low-quality area. A retinal structure activation (RSA) module to protect retinal structure characteristics and guide the reconstruction processing. The decoding operator immediately extracts the characteristics. For the primary components of the retina, such as the vessel, optic disc, and cup regions, the RSA module forecasts a segmentation mask map.This method reached the accuracy of 0.951 and the sensitivity around 0.600.

In 2019, Toufique Ahmed Soomro and Ahmed J. Afifi proposed a new method of accurate detection of retinal blood vessels based on a deep convolutional neural network (CNN) model[6]. There employs a U-Net architecture, a popular CNN design for image segmentation, and trains it using a dataset of retinal fundus images that is openly accessible. Suggested an image enhancement method for the enhancement of vessels during the pre-processing stage. This will reduce the pictures' erratic lighting and enhance their low and variable contrasts. The first stage is to choose an RGB channel with goodcontrast; the second is to remove the uneven illumination using a morphological operation; and the third is to remove the noise using a fuzzy C-Mean. The final stage involves using CLAHE to obtain a well-contrasted image. Instead of working directly with the color pictures, the descriptors are extracted from the grayscale representation. The color retinal fundus image is converted to a grayscale format using the defined processing method in order to acquire an appropriate input image for processing each color channel. For further analysis and training, the green channel was chosen. The retinal fundus image's background includes variations in the intensity level; however, these background changes must be consistent if the retinal blood vessels are to be successfully trained and segmented. For this, top-hat transform and bottomhat transform morphological procedures were used. Even after using these transforms, noise still exists, making it challenging to analyze large vessels and even more challenging to analyze tiny vessels. This issue can be resolved by using fuzzy Cmeans (FCM) to reduce background noise so that both typical and small, low-contrast vessels can be seen more clearly. A deep modified U-Net model with a few extra layers to produce the segmented vessel picture was used for retinal vessel segmentation. An encoder part and a decoder element make up this network. The decoder reconstructs the output as a segmented vessel image using the features that the encoder used to extract the features that describe the input image. The final binary picture is produced by the morphological reconstruction process. On the DRIVE and STARE databases, this technique achieved accuracy of 0.959 and 0.961, respectively, and sensitivity of 0.80 on both databases.

Xiaomeng Li and Xiaowei Hu in 2019 proposed a crossdisease attention network (CANet) for jointly grading diabetic retinopathy (DR) and diabetic macular edema (DME) in retinal fundus images[7]. The author uses a dataset of retinal fundus images and trains the proposed CANet using a multi-task learning approach. The author notes that their model outperforms current approaches for both DR and DME grading when comparing the performance of their proposed model with other cutting-edge techniques. Additionally, they designed a powerful disease-dependent attention module to effectively capture the internal relationships between two diseases. They suggested the disease-specific attention module to carefully learn useful features for individual diseases. In order to pinpoint the areas of the picture that are crucial for the classification choice, the author also conducted an analysis of the attention maps produced by the CANet. They proposed that by using this analysis, the decision-making process of the model could be better understood.

In the same year, Karthik Gopinath and Jayanthi Siva Swamy proposed a method for segmenting retinal cysts from optical coherence tomography (OCT) volumes[8]. They applied a selective enhancement technique to the cyst areas of the OCT volume. A convolutional neural network (CNN) is then given the improved image to segment the cysts. In general, various operator-defined protocols are used to acquire the volumes of spectral-domain optical coherence tomography (SD-OCT). As a result, there are significant differences in the acquired volumes' layer orientation, resolution, and number of segments. This variability was addressed by standardizing the size of each slice to 512 x 256 pixels through resizing. For each volume, a rough region of interest (ROI) was determined as follows because the region of interest only occupies 0.40 of each slice: each slice image was projected along columns to obtain a 1D profile of the image. A Gaussian was fit to this profile to obtain the mean region with higher intensity. The signal from the SD-OCT volumes is usually affected by speckle noise. A total variational denoising method was used to denoise all ROIs. This reduces the texture content and results in a smoother image. Cysts are known to be restricted to the layers between Internal Limiting Membrane (ILM) and Retinal Pigment Epithelium (RPE). An accurate, graph-based segmentation approach was used to extract only the ILM and RPE layers to form a mask. This mask serves as a position prior in the detection stage. The selective enhancement process was used for localization of the objects of interest. This was done by employing the notion of Generalized Motion Pattern (GMP). The CNN architecture is designed to utilize neighborhood information The CNN architecture's first stage reduces the 3D data to a 2D grid without any contextual information. A wide field of view is evaluated in stage 2 at a smaller scale to combine 3D data with a 2D map. The third stage, which improves the boundary information at the initial scale, uses the output of stage 1 in combination with the second input (Input 2). The output from stages 2 and 3 are combined to create the input for the last step. To address the class disparity in the data, a weighted binary cross-entropy loss function was selected. A rough region around the objects of interest (cysts), rather than precise cyst regions, is identified due to the smearing impact of GMP.Therefore, segmentation is necessary to determine the exact cyst border. To create a binary map depicting the regions of detected cysts, the probability map is thresholded. In order to extract the detected regions from the intensity space, this map is multiplied by the ROI picture. In the intensity space, detected areas are grouped into cysts, false positives, and background. The clusters with a lower mean intensity are kept as desired cyst segments because cysts are relatively darker regions compared to false-positive regions.

Yi-Wei Chen and Tung-Yu Wu in 2018 proposed a deep convolutional neural network (CNN) model for the detection of diabetic retinopathy[9]. The framework consists of three important components: the preprocessing step, the classification network, and the post-prediction. The region of interest (ROI) detection and picture enhancement processes are two additional divisions of the preprocessing stage. The background information in the raw fundus pictures is useless. Based on the assumption that the background tends to be black, I performed Otsu's threshold to find the regions of interest (ROI). The image enhancement draws attention to details like microaneurysms and hemorrhages that are associated with DR symptoms. The classification network's objective is to categorize the DR severity grades. This proposed classificationmodel is based on previous DCNN designs. With 10.4 million parameters, this model has 15 convolutional layers and five pooling layers. Used mostly 3 x 3 filters, and after each layer of pooling, doubled the number of channels. Rather than using completely connected layers, global average pooling and 1 x 1 filters were used to regularize the model and decrease the number of parameters. Additionally, sequential normalization was used to reduce the generalization gap and speed up convergence after each convolutional layer. Finally, the post-prediction effectively addresses the issue of various DR grading schemes. The accuracy of this technique was 0.905.

In 2016, Harry Pratta and Frans Coenen explored the use of convolutional neural networks (CNNs) for the detection and classification of diabetic retinopathy (DR) in retinal fundus images[10]. Images from patients representing a wide range of ages, ethnicities, and lighting conditions were included in the dataset. The dataset was downsized so that it would fit in the system's memory while still preserving the complex characteristics that were intended to be identified. The CNN was initially pre-trained. This was required in order to obtain a classification result reasonably quickly without significantly increasing training time. The network was trained on the complete set of training images for an additional 20 epochs after completing 120 epochs of training on the original images. Over-fitting is a serious problem for neural networks. Realtime class weights were introduced in the network to address this problem.The class weights were updated for each group loaded for back-propagation with a ratio corresponding to the number of images in the training batch that were identified as showing no signs of DR. This significantly reduced the possibility of over-fitting to a specific class. Using stochastic gradient descent and Nestrov momentum, the network was trained. The weights were stabilized using a low learning rate of 0.0001 over a period of five epochs. The accuracy of the model was then raised to over 0.60, which required about 350 hours of training, by increasing this to 0.0003 for the substantial 120

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epochs of training on the original images. The network was then trained using a low learning rate on the entire training collection of images. The precision of the network reached over 0.70 after a large number of epochs with the entire dataset. The learning rate was then lowered by a factor of 10 every time training loss and accuracy saturation occurred. The network was trained only once using the initial, preprocessed images. The network's localization performance was then enhanced during training by using real-time data supplementation. Each image was randomly enhanced during each epoch with random rotations of 0–90 degrees, random yes–or–no flips of the horizontal and vertical axes, and random shifts of the horizontal and vertical axes. The final trained network had a final precision of 0.95, an accuracy of 0.75, and a sensitivity of 0.30.

III. CONCLUSION

The weighting and placement of various characteristics are necessary for classifying DR. The phases of DR are determined by the kind of lesions that develop on the retina. This is highly time-consuming. An ophthalmologist can determine whether a patient is infected or not using a machine learning model that assists in the detection of disease stages and the recognition of retinopathy disease based on symptoms and degrees of disease segmentation and classification. Automatic screening techniques significantly sped up the diagnosis process, saving time and money while also allowing patients to start their treatments sooner. The most recent automated deep learning-based systems for diagnosing and categorizing diabetic retinopathy have been reviewed in this article.

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