Diabetic Retinopathy Detection and Classification using CNN Techniques

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Abstract:

A common diabetes consequence and the world's leading cause of blindness is diabetic retinopathy (DR). Early detection and accurate diagnosis of DR are necessary for rapid treatment and preventing vision loss. Convolutional neural networks (CNNs) have emerged as powerful tool for automated DR detection and classification from retinal fundus images. This survey paper gives a thorough analysis of the material already in existence on CNN-based techniques for DR detection, covering various aspects including dataset acquisition, preprocessing, network architectures, training strategies, performance evaluation, challenges, and future directions. The purpose is to present a consolidated view of the state-of-the-art CNN algorithms for DR detection, highlight key research findings, discuss challenges faced in this domain, and suggest prospective research trajectories.

1. Introduction:

Diabetic retinopathy is an advanced eye disease that marks individuals with diabetes, causing damage to the retinal blood vessels. Early detection and effective management of DR are crucial to prevent vision loss. This section provides an introduction to DR and outlines the importance of automated detection and classification approaches based on deep learning. This section introduces the significance of automated DR detection and the role of CNN algorithms in addressing this problem. It provides an overview of DR and its impact, emphasizing the need for efficient and accurate detection methods. Diabetes Mellitus (DM) patients are much more likely to become blind than people without DM. DR is a silent illness that only becomes apparent in its advanced stages, when it is very difficult or even impossible to treat. In DR, blood vessels that supply the retina begin to leak fluid and blood onto the retina, causing visual lesions like microaneurysms, haemorrhages, hard exudates, cotton wool patches, and blood vessel area lesions. The retinal blood vessels' elevated sugar level condition leads to microaneurysms (MAs). MA is an early sign of diabetic retinopathy, which may be regarded a basic element of diabetic retinopathy. A shape of MAs is almost circular with darkish color and is tiny in size.

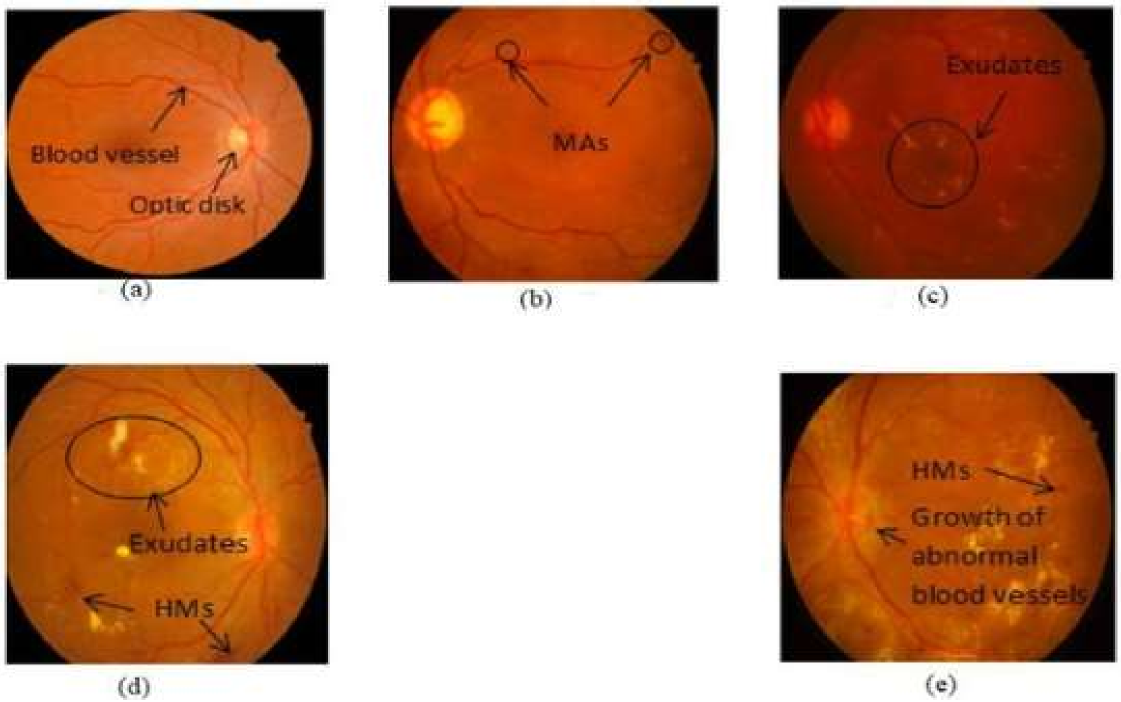

Figure 1: a) Normal retina b) Mild NPDR c) Moderate NPDR d) Severe NPDR e) PDR.

One of the most severe DR causes is the presence of exudates in the retinal fundus images. MAs are also the early signs of because of retinal vasculature widening. Figure 1 shows the a visual depiction of the normal retina and different levels of DR. Since each stage has unique symptoms and characteristics, doctors cannot now identify the DR stages from normal photos. Only when it is caught early enough can it be adequately treated, thus early detection through routine screening is crucial. Given how expensive this process is, automatic screening is crucial to reducing manual effort. Automated digital picture capture and image processing techniques should be used to detect deviations in retinal images so that it is cost-effective.

Moreover, the current procedures for diagnosis are quite ineffective because they take a long time, which can cause the treatment to fail. Doctors employed fundus cameras, which take pictures of the veins and nerves behind the retina, to detect retinopathy. It is extremely difficult to identify this disease in its first stages because the disease's initial stages show no symptoms of DR. We have employed various CNN (Convolutional Neural Network) algorithms for early detection so that medical professionals can initiate treatment at the appropriate moment.

2. Literature Survey:

In accordance with the survey results, many experts have declared that almost 90% of people with diabetes can be saved by detecting diabetic retinopathy early [8]. The finding of DR can be manually performed by ophthalmologists and also can be done by an automated system. Since diabetic retinopathy marks are much smaller in size in the early stages, the chances of being left unidentified is more in manual detection. Discovering diabetic retinopathy through an automated system is much more authentic, reliable, faster, efficient and easier than the manual system.

Diabetic Retinopathy (DR) is caused as a result of Diabetes Mellitus which causes development of various retinal abrasions in the human retina. These lesions cause hindrance in vision and in severe cases, DR can lead to blindness. DR is observed amongst 80% of patients who have been diagnosed with prolonged diabetes for a period of 10–15 years. The manual process of periodic DR diagnosis and detection for necessary treatment is time consuming and unreliable due to the unavailability of resources and expert opinion. Therefore, computerized diagnostic systems which use Deep Learning (DL) Convolutional Neural Network (CNN) architectures, are proposed to learn DR patterns from fundus images and identify the severity of the disease. In order to examine and evaluate the performance of 26 cutting-edge DL networks and to contribute to deep feature extraction and image classification of DR fundus pictures [1], the research provides a comprehensive model. ResNet50 has demonstrated the most overfitting in the proposed model, whereas Inception V3 has demonstrated the lowest overfitting when trained using the Kaggle's EyePACS fundus picture dataset.

On a sizable dataset of roughly 3662 train images, CNN, hybrid CNN with ResNet, and hybrid CNN with DenseNet are utilised to automatically identify the stage of DR that has advanced. In the proposed study, five DR stages—0 (no DR), 1 (mild DR), 2 (moderate), 3 (severe), and 4 (proliferative DR)—are processed. The model receives input from the patient's eye pictures. To extract the properties of the eye for efficient categorization, deep learning architectures including CNN, hybrid CNN with ResNet, and hybrid CNN with DenseNet 2.1 are proposed. The models' respective levels of accuracy were 96.22%, 93.18%, and 75.61%. In the [2] paper's comparative analysis of CNN, hybrid CNN with ResNet, and hybrid CNN with DenseNet architectures, the winner for the best deep learning classification model for automated DR detection is hybrid CNN with DenseNet.

Numerous varieties of ResNets are utilised, each with a different number of layers—specifically, 18, 34, 50, 101, and 152 layers—to address the classification difficulties [7]. ResNet-50 [6] is the current deep learning framework for identifying and rating DR. Overfitting and accuracy variations, which have an impact on ResNet-50's accuracy in identifying DR, are its drawbacks. Three methods are suggested in this study to raise ResNet-50's performance: 1) ResNet-50's adaptive learning rate. 2) Regularisation: Regularisation can be used to reduce the training model's overfitting. 3) In ResNet-50, obtain the appropriate characteristics from conv5_block1_out and conv5_block2_out.

The suggested [8] method employs Random Forest and deep ResNet-50 features as a classifier for the identification and grading of diabetic retinopathy. A trained ResNet-50's average pooling layer yields high-level characteristics that are supplied to a random forest classifier. The performance of the deep networks is critically dependent on their depth. The performance of the model improves as the number of layers increases[7]. The presence of additional layers, however, has also been seen to potentially raise error rates. This is referred to as a vanishing gradients problem. To solve this issue, the residual neural network, often known as ResNet, was developed. Residual Network addresses the issue of vanishing gradients by using the skip connection to arbitrarily permit some input to the layer to absorb the flow of information and also to prevent its loss (which also suppresses the development of some noise). Averaging the models maintains a balance between precision and generalization while suppressing the noise. The most effective method is to increase the amount of labeled data in order to get higher precision and an approximated degree of traversal. The ResNet structure facilitates ultra-deep neural network training and improves model accuracy on enormous training datasets. The following are the results of prior research that are compared to the most recent studies in Table 1:

Table 1: Comparison of various results

Author	Methodology	Sensitivity	Specificity	Accuracy
Pravin R. Kshirsagar et.al	GLCM	96.15%	95.65	95.91%
R. K. Yadav et.al	Resnet-50	95.99	99.16%	97.52%
S. M. Boudiaf et.al	VGG16	92.75%,	96.8%,	94.1%
Mahmut Karakaya et.al	Transfer learning using smartphone-based retina imaging systems	95.91%	95.65%	94.1%
J. A. Moreno et.al	UNET	98%	98%	97%

3. Diabetic Retinopathy Datasets:

A comprehensive review of publicly available datasets for DR research is presented, including their characteristics, strengths, and limitations. This section discusses widely used datasets such as the Kaggle Diabetic Retinopathy Detection (Kaggle DR) dataset, the Messidor dataset, and others, highlighting their importance in developing and evaluating CNN-based algorithms. A Dataset is collection of records containing useful information, such as insurance or medical records applied by a set of instructions on the system [14]. In this review, all the datasets related to diabetic retinopathy are discussed. The DR datasets contain the records in the form of fundus images. Most researchers employed accessible publicly available data sets by the specific links. In the experiments, several total images are reserved for the training dataset and some are assigned for testing purposes. For example, Tan, Fujita [15] applied 298 images of CLOEPATRA dataset to classify diabetic retinopathy, wherein half the total number of photos were designated for training and the other half for testing. In the same way, Yang adopted the Kaggle dataset, which is a public dataset contains 22,795 fundus images. The utilization purpose of the Kaggle dataset was to classify the diabetic retinopathy. In the experiments, 21995 800 fundus images were assigned for testing after using fundus photographs for training.

4. Preprocessing and Data Augmentation

To minimize bias, deep learning techniques are applied to the need for handcrafted features and, therefore pre-processing steps. However, in some DNN studies, some pre-processing steps for enhancing and enhancing picture quality are relevant. Additionally, several pre-processing techniques for identifying the region of interest in images are used commonly.. Resizing is the most utilized pre-processing step. The basis for this is to make the images appropriate for the input size of CNN. Resizing is followed by normalization and cropping, as expected. Normalizing is performed to promote the DNN learning process, make the training faster, and avoid overfitting. Further, cropping improves success by reducing the contribution of the background to the process of training.

Data augmentation is a commonly performed technique within deep learning applications to reduce overfitting because of the limited training data set and increase the algorithm’s performance by increasing a measure of data. conventional methods for data augmentation are translation, stretching, flipping, zooming, contrast adjustment, and rotation. In most of the studies, Conventional methods of data augmentation are used, however, in a minority of the studies, different approaches are used. Nevertheless, the effect of data augmentation in DR classification is still a question mark and needs further investigation.

5. Diabetic Retinopathy Features:

The various features of diabetic retinopathy are listed as follows:

Microaneurysm (MA): The Microaneurysm (MA) is the earliest characteristic that may be seen in DR. MA is a little, rounded object with dark red markings. Sharp margins with a size between 20 and 200 m are typical for MA. The development of retinopathy and retinal ischemia are caused by an increase in microaneurysms. The aberrant permeability of the retinal blood vessels is the primary factor in the development of MA. In addition to waking up the vessel wall, microaneurysms can obstruct retinal blood vessels. These microaneurysms have the potential to burst, bleeding. The MA are traits that can always be seen or recognised in the early phases of DR, whereas the haemorrhages could be found in more advanced phases, according to an international classification of DR levels of severity.

Hemorrhages: The second sign of DR is haemorrhages (HEM), which result in pressure on the blood vessels and produce bleeding of a jelly-like substance in the centre of the eye. HEM are primarily brought on by a weak vessel leaking. Similar to the MA, HEM appear as a red patch with a variable density and irregular edge. Its dimensions are 125 mm. Flame and dot-blot HEM (DBH) are the two types into which HEM are typically divided. In the first form, the HEM originates from the precapillary arterioles and emerges at the nerve fibres. In contrast, the DBHs are rounded and smaller than MA. DBHs can appear at various levels of the retina and happen at the capillary's venous end.

Hard exudates: The third indication of DR are yellowish, amorphous, glossy hard exudates (HE). Unlike MA, HE can exist inside the retina and, when it does, it causes proteins and lipoproteins to seep from the retinal capillaries. HEs often appear as a circular ring next to the

MA and are most frequently found in the outer layer of the retina. Figure 3 provides an illustration of these traits in photographs of the human retina.

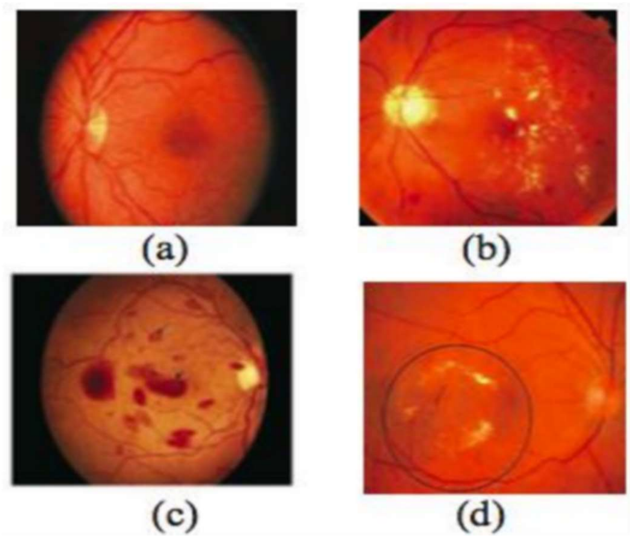

Figure 2: Retina of eye (a) Normal retina(b) Microaneurysm (c) Hemorrhage (d)Hard exudates.

6. Diabetic Retinopathy Detection Techniques:

The retinal image input is fed to the preprocessing techniques applied to retinal fundus images before submitting them to CNN algorithms. It discusses image resizing, normalization, color correction, and other preprocessing steps aimed at enhancing the input data and enhancing the CNN models' performance. Later the various CNN architectures employed for DR detection. It covers popular architectures such as AlexNet, VGGNet, GoogLeNet, ResNet, and DenseNet, highlighting their strengths, architectural variations, and their effectiveness in overcoming the obstacles of DR detection. Here the training strategies used to make CNN models more effective at DR detection. It includes methods like data augmentation, transfer learning, and fine-tuning. Discussions of these tactics' benefits and drawbacks are included, along with suggestions for obtaining peak performance.

An analysis of metrics for performance evaluation assessing the effectiveness of CNN models in DR detection is presented. The survey covers metrics such as accuracy, sensitivity, specificity, precision, and area in the region under the receiver operating characteristic curve (AUC-ROC), providing insights into their interpretation and comparative analysis. The restrictions and difficulties faced in CNN-based DR detection covers concerns regarding dataset bias, class imbalance, interpretability of CNN models, generalization to diverse populations, and robustness to image quality variations.

7. Conclusion:

The paper covers a detailed survey about diabetic retinopathy identification by collecting retinal datasets and adopts to different methodologies to detect DR. Initially, retinal datasets are discussed and then several kinds of approaches have been explained to detect retinal abnormalities including retinal neovascularization, hemorrhages, microaneurysm, and exudates. by summarizing the key findings and contributions of the survey. It emphasizes the significance of CNN algorithms in DR detection, highlights challenges and limitations, and presents suggestions for additional research to further enhance the accuracy and usefulness of automated DR diagnosis using CNN techniques. This survey paper serves as a comprehensive source for academics and medical professionals, and practitioners interested in the application of CNN algorithms for diabetic retinopathy detection. It consolidates state-of-the-art techniques, identifies research gaps and challenges, and offers prospective directions for the future exploration and innovation in this important field.

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