Deep Learning - Based Diabetic Retinopathy Detection: A Survey on Deep Learning Architectures

Dr. Srinidhi G. A.

Assistant Professor, Department of ETE, Sri Siddhartha Institute of Technology, Sri Siddhartha Academy of Higher Education, Tumkur – 572102, India.
Email: *srinidhiga[at]ssit.edu.in*

Abstract: ***A degenerative eye disorder Diabetic Retinopathy (DR), a condition that damages the retina occurs when blood glucose levels remain consistently high. It is necessary to detect the DR in the early stages to minimize future losses. Deep learning algorithms can analyze retinal fundus images, which helps in the early diagnosis of DR. This research looks at how deep learning approaches are used to recognize and classify retinal fundus images. In this paper, different deep - learning algorithms are studied to detect the presence of Diabetic Retinopathy. We examined different approaches in this study and evaluated the gaps in the literature about DR detection and classification, outlining their benefits and drawbacks. We also emphasize the challenges that lie ahead in developing robust, reliable, and effective deep - learning algorithms for diagnosing various Diabetic Retinopathy issues, as well as possible directions for future research.***

Keywords: Deep learning, CNN, GoogleNet, AlexNet, VGGNet, RELU

1. Introduction

Diabetic Retinopathy is one of the most prevalent eye conditions (DR) and one of the primary causes of blindness. Approximately 422 million individuals globally suffer from diabetes. A significant portion of these individuals have diabetic retinopathy, and diabetes is directly responsible for 1.5 million annual fatalities Diabetic Retinopathy can result in loss of vision and eventually lead to blindness in diabetic patients.

Since DR is undiagnosed or only manifests extremely weak symptoms, it can be challenging to identify at the beginning, which leads to the person subsequently damaging their eyesight. Early diagnosis is essential for Diabetic Retinopathy (DR) since the treatment is possible if the condition is diagnosed early. However, it is crucial to remember that DR becomes incurable at an advanced stage. The DR treatment at its early stage slows down the retinal microvascular degeneration process.

Traditional DR detection approaches are time - consuming, expensive, and require regular checkups of the retina. Therefore, a more affordable, and effective diagnosis is required. The money and effort can be saved by automating the DR detection using retinal fundus images by applying deep learning approaches. Due to the large number of patients and the scarcity of qualified professionals, early detection of DR is crucial yet challenging in the medical sector. Many researchers were inspired by this to create a computerized automated approach for analysing retinal fundus images. Compared to existing computer vision approaches, automatic DR detection systems based on deep learning technologies have demonstrated a more significant accuracy. This study examines the most recent deep - learning techniques for DR detection and highlights the contributions and challenges of the reviewed research papers.

2. Problem Statements

Conventional methods require manually screening fundus images and identifying the presence of DR. The disadvantage of manual screening is that the diagnosis of fundus images entails a significant amount of time, effort as well as expertise, which is susceptible to errors. The potential for severe damage to occur is high if the ophthalmologist lacks extensive knowledge of the procedure. Therefore, to facilitate early detection and effective prevention, it is necessary to implement an automated, precise, and efficient method for identifying abnormalities in retinal fundus images.

3. Objectives

In the past few years, the way DR is found has changed from using more traditional machine learning methods to using deep learning methods like convolutional neural networks (CNN).

1) Create a deep learning model that can accurately find lesions, look at signs like microaneurysms, exudates, and hemorrhages, and group the different stages of DR. It is important to find out where lesions appear and how often they emerge.
2) Look at how well each CNN model does over a few epochs.
3) Make a difference in the medical field by creating an automatic, low - cost way to detect DR in the early stages and save individuals from permanent blindness. The goal is to find lesions in fundus images and classify DR stages more accurately by using digital fundus images and deep learning approaches.

4. Outline of Deep Learning Techniques

One widely used deep learning architecture for detecting DR is the Convolution neural network (CNN). CNN is widely used for computer - aided DR detection. A convolutional neural network is a feed - forward neural network that is widely used for generalizing vision - related problems. It is commonly called ConvNet and usually contains an input layer, hidden layer, and output layers and is widely used in image processing and identification. To aid in the process of information extraction from images, a CNN employs several hidden layers. In convolutional neural networks (CNNs), the four most crucial layers are convolution, reLU, pooling, and fully connected ones. For a convolution tool to analyze an image, it must first extract and identify its many features. This process is called feature extraction. Using the convolutional process's output, a fully connected layer may determine the image's classification using data that has already been retrieved. It was in 1988 when LeNet, the first convolutional neural network, was introduced. We used LeNet to accomplish character recognition tasks, such as reading numerals and zip codes. Two fully linked layers and five convolutional layers comprise this model.

The vanishing gradients made it difficult for this model to train.5 max - pooling layers, 3 fully linked layers, and 2 dropout layers make up the AlexNet network. Though this architecture is quite identical to LeNet, but much deeper stacked layers. AlexNet architecture is deeper than LeNet - 5 and utilizes the ReLU activation function. GoogLeNet architecture used by Google in 2014 has models with a reduced error rate. With 16 layers of CNN and up to VGGNet 95 million parameters, can operate on 4096 convolutional features and can be trained on more than one billion pictures. It is too expensive to train and needs huge data. The most complex network has ResNet architecture, which has 152 layers, 32 GPU power, and can train over many months. MobileNets have made it possible to implement convolutional neural networks (CNNs) on mobile devices, allowing for better image processing and smaller latency. Unfortunately, medical domains, especially those dealing with DR detection, do not have access to the massive volumes of data needed to train a CNN model [1]. We can solve this problem by using transfer learning. Utilizing a pre - trained convolutional neural network (CNN) model as a feature extractor and then fine - tuning it with domain - specific data are often used transfer learning strategies. Full convolutional neural networks (FCNs) are an alternative to CNNs that utilize deconvolution layers to make the output map the same size as the input image [2]. This is done by reversing the down - sampling process that happens in convolutional layers. The usage of this method for segmentation is widespread.

4.1 Image Processing

Pre - processing retinal pictures prepared them for testing and training. Image preprocessing and grayscale separation are the most crucial steps. Gamma correction and CLAHE improved the image quality. Pre - processing removes noise and poor contrast from the image. Morphological Opening (MO) may remove small components from retinal fundus images without changing their form or size. Avoid noise overamplification via contrast - limited Adaptive Histogram Equalization (CLAHE). CLAHE (Contrast - limited Adaptive Histogram Equalization 21) improved contrast and removed noise from APTOS images. Gamma settings may minimize color cast in photos. The DRIVE dataset included pre - compressed and resized view field - optimized JPEGs. Gaussian Blur reduces retinal fundus noise and resolution, whereas Local Thresholding converts grayscale to black and white.

5. DR Detection

In the image - screening process, the fundus image may be either classified as normal or show the presence of DR using fundus image - based detection. This is among the first domains of medical diagnostics where Deep Learning has produced noteworthy advancements.

5.1 Types of Diabetic Retinopathy

When it comes to diabetic retinopathy, there are two main categories:

1) Non - Proliferative Diabetic Retinopathy (NPDR): Develops vision changes early. Damage to the retina's pericytes occurs as a result of hyperglycemia, or an abnormally high blood sugar level. These retinal pericytes are specialized contractile cells surrounding the retinal vasculatures and play a crucial role in facilitating blood circulation to the retina. The damage to these pericytes is believed to be caused by an inability to properly metabolize the glucose within the cells and this results in osmotic damage. This damage to the retinal pericytes is the early stage of DR.

2) Proliferative Diabetic Retinopathy (PDR): Vascular proliferation inside the retina is a feature of proliferative DR. This is because ischemia (ischemia is the lack of oxygen supply to the cells of the retina), caused by the microvascular damage that appears in the first stage of DR, leads to this proliferation. Now the retina tries to compensate for this ischemia by producing a growth factor known as VEGF (Vascular Endothelial Growth Factor). VEGF starts to produce abnormal new blood vessels. Neovascularization is the process by which the blood vessels in the retina get bigger and bulge out toward the vitreous. Unfortunately, when the DR hits this stage, it results in potentially vision - threatening complications such as vitreous hemorrhage or retinal detachment.

5.2 Grading of DR:

To classify the severity of the DR, the fundus images are categorized into different Diabetic retinopathy stages ranked by severity.
- No DR
- Mild NPDR
- Moderate NPDR
- Severe NPDR
- PDR

6. Literature Survey

Various studies have tried to use Deep Learning methodologies to identify and classify DR lesions automatically.

6.1 Lesion Detection and Segmentation Approaches

Many DL approaches for identifying and diagnosing various forms of DR lesions, including macular edema, exudates, and microaneurysms, have been presented. These methods are discussed in this section.

6.1.1 DR and Macula Edema Detection Approaches

Sundaram S et al., [3]. introduces a novel approach to automatically identifying and categorizing DR and DME from retinal images in their research. The "Harris Hawks optimization (HHO) " methods are used in this strategy to boost the contrasts of the image. The authors of this paper automated the diagnosis of DR and DME by using an Ensemble Convolutional Neural Network (ECNN). The proposed model represents a significant step forward in the automated deep learning - based identification of DR and DME with an accuracy of 99%, and it has shown promising results when tested on two publically available datasets, Messidor and IDRiD.

Researchers XSingh RK and Gorantla R introduced modules in their research [4] for assessing DR and DME simultaneously. suggest a new DMENet Algorithm that leverages the foundational principles of CNNs. DMENet uses two - phase processing to handle and analyze the color fundus images that have already been preprocessed. The initial phase is to check for the occurrence of DME, and the next phase is to grade the images according to severity. In both phases, an innovative Hierarchical Network of CNN (HE - CNN) is used. Messidor and IDRiD, two industry - standard datasets, were used to evaluate the model. The suggested technique attained an average Accuracy of 96.12%, Sensitivity of 96.32%, Specificity of 95.84%, and F - 1 score of 0.9609.

To identify diabetic macular edema (DME), Amit kumar et al., [5] developed a technique to categorize the severity of DME grades using Squeeze - and - Excitation embedded DenseNet121 (SEDense). The procedure begins with pre - processing steps like augmentation and green channel extraction. With just 413 input images to work with, the enhancement yields 1170 final images. A total of 103 fundus images of the retina are used to evaluate the SEDense. The "Diabetic Retinopathy - Segmentation and Grading Challenge" at ISBI - 2018 showcased many state - of - the - art models; nevertheless, SEDense proved to be the most effective. With an accuracy of 88.35%, it categorizes the DME grades. Diagnosing DME grades is made easier for ophthalmologists using the suggested SEDense model.

Table 1: Illustrates different DR and Macula Edema Detection Approaches

Research paper	Dataset	Methodology	Segmentation	Performance
Sundaram S [3]	Messidor IDRiD	Ensemble convolutional neural network (ECNN)	DR and DME	Accuracy=99%
XSingh RK at el., [4]	Messidor IDRiD	HE_CNN	DR and DME	Accuracy=96.12%, Sensitivity=96.32%, Specificity=95.84, F - 1 Score=0.9606.
Amit kumar et al., [5]	IDRiD	DenseNet121 (SEDense)	DME grades	Accuracy=88.35%

6.1.2 Microaneurysm Detection Approaches

The suggested method by Mateen, M et al., [6] detects MAs early utilizing a hybrid feature embedding strategy comprising pre - trained CNN models called VGG - 19 and Inception - v3. The suggested approach's performance was evaluated using publicly available datasets, namely "E - Ophtha" and "DIARETDB1, " and it achieved 96% and 94% classification accuracy for microaneurysm identification, respectively.

The suggested approach by Long, S., Chen, J., Hu, A. et al., [7] was trained and tested by applying the E - ophtha MA database, and it was then tested again using another independent DIARETDB1 database. The findings of microaneurysm detection on the two datasets were analyzed on a lesion - by - lesion basis and compared with existing techniques. The area under the curve (AUC) of the receiver operating characteristic (ROC) curve was 0.87 and 0.86, respectively, in both cases.

Sheikh Islam, Md. Mahedi Hasan and Sohaib Abdullah developed a novel deep convolutional neural network (CNN) in the research [8] that can detect the occurrence of microaneurysms from the fundus images which are usually the initial signs of diabetic retinopathy (DR). After tracking the microaneurysms, the model categorizes them into five stages, ranging from No DR to PDR on one of the most freely accessible datasets Kaggle, their network achieved amazing results. To be more precise, the proposed design attained the kappa score of 0.851 with a new standard for severity rating and an AUC of 0.844. The model also achieved a sensitivity of 98% and a specificity of 94%.

Table 2: Illustrates different Microaneurysm Detection Approaches

Research paper	Dataset	Methodology	Segmentation	Performance
Mateen, M et al., [6]	E - Ophtha and DIARETDB1	VGG - 19 and Inception - v3	Microaneurysm identification	E - Ophtha Accurany=96%, DIARETDB1 Accuracy=94%
Long, S., Chen, J., Hu, A. et al. [7]	E - Ophtha and DIARETDB1	directional local contrast (DLC)	Microaneurysm detection	AUC= 0.87, ROC=0.86
Sheikh Islam et al., [8]	Kaggle	CNN	Microaneurysm detection	Kappa score=0.851, AUC=0.844, Sensitivity=98%, Specifity=94%

6.1.3 Hemorrhages Detection Approaches

Hemorrhages have also bee-n explored as an indication of DR utilizing Deep Learning methods, as shown in this section.

The method of Maqsood S et al. [9] deliberated in the Exudate section to extract features from identified hemorrhages, a modified pre - trained CNN architecture is used. The suggested method is tested on 1509 photos from the HRF,

Paper ID: SR24805160228 DOI: https://dx.doi.org/10.21275/SR24805160228

DRIVE, STARTTE, MESSIDOR, DIARETDB0, and DIARETDB1 databases, and it achieves an average accuracy of 97.71%, outperforming prior research. Furthermore, the suggested bleeding detection system outperforms state - of - the - art approaches in terms of visual quality and quantitative analysis with high accuracy.

One way to segment retinal fundus images to locate hemorrhages is the approach presented in the work by Aziz, T. et al., [10]. The first step of the proposed method is to acquire retinal fundus images. The lesions are then divided up using an innovative adaptive threshold based on smart windowing. The last step is to use a support vector machine to extract and classify all the candidate's conventional and hand - crafted characteristics. The proposed method achieves a high F1 score, with DIARETDB1 showing an F1 score of 83.85% and DIARETDB0 showing an F1 score of 72.25%. As a segmentation tool, the proposed method adapts well when compared to conventional techniques.

A modified CNN UNet architecture is presented in this research by Skouta et al, [11] for detecting retinal hemorrhages in fundus pictures. Using the GPU and the IDRiD dataset, the proposed UNet was trained to segment and identify potential regions that may harbor retinal hemorrhages. The experiment was also run with the IDRiD and DIARETDB1 datasets, which are both publicly available on the Internet. The learning neural network then showed a substantial improvement, effectively segmenting the bleeding and achieving sensitivity, specificity, and accuracy of 80.49%, 99.68%, and 98.68%, respectively. In addition, the trial results revealed an IoU of 76.61% and a Dice value of 86.51%.

Table 3: Illustrates different Hemorrhages Detection Approaches

Research paper	Dataset	Methodology	Segmentation	Performance
Maqsood S et al. [9]	HRF, DRIVE, STARTTE, MESSIDOR, DIARETDB0, and DIARETDB1	CNN	Hemorrhages identification	accuracy of 97.71%
Aziz, T. et al., [10]	DIARETDB0, DIARETDB1	CNN	Locate Hemorrhages	F1 score of DIARETDB1= 83.85%, F1 score of DIARETDB0=72.25%.
Skouta et al, [11]	IDRiD, DIARETDB1	UNet	Identifying Hemorrhages	Sensitivity=80.49%, Specificity=99.68%, Accuracy 98.68%.

6.1.4 Exudates Detection Approaches

Image preprocessing, dimensionality reduction, and feature extraction are among the key pre - processing stages used in Exudates detection. The green channel has the highest contrast across ocular tissues such as OD and BV. The green channel is used to examine eye abnormalities, and the details are more obvious in the green channel than in the other retinal images. As a result, the green channel is regarded as the principal source component for EX detection [12]. Once the green channel picture has been extracted, it is necessary to enhance the retinal image's quality. The fundus image contrast is enhanced using CLAHE, which stands for contrast - limited adaptive histogram equalization. The quantity of false positives while detecting Exudates may be decreased by localizing the OD. Finding the highest intensity point in the median - filtered fundus image allows for OD localization, and the OD radius is four times the Area of interest.

The current study by W. Auccahuasi et al., [13] proposes a novel method for automatically identifying hard exudates in retinal images utilizing a Convolutional Neural Network and the DIARETDB1 database, two checks are performed on the classifier using similar groups of images, such as the group of tests and validation, yielding sensitivity values of 0.92% in both cases and specificity values of 0.92%, and 0.93% for the groups of test and validation images, respectively.

To improve the efficiency of automated exudate identification, Parham Khojasteh et al., [14] evaluated supervised and unsupervised classifiers, CNNs, ResNet - 50, and Discriminative Restricted Boltzmann Machines that had been pre - trained. Two open - source databases, DIARETDB1 and e - Ophtha, were used for the analysis. Relatively compared to other networks, ResNet - 50 with Support Vector Machines achieved a sensitivity level of 0.99 and an accuracy of 97.6%. ResNet - 50 can be useful for efficiently detecting exudates in fundus images.

Table 4: Illustrates different Exudates Detection Approaches

Research paper	Dataset	Methodology	Segmentation	Performance
W. Auccahuasi et al., [12]	DIARETDB1	CNN	Hard exudates in retinal images	Sensitivity=0.92 Specificity=0.93
Parham Khojasteh et al., [13]	DIARETDB1 and e - Ophtha	CNNs, ResNet - 50, and Discriminative Restricted Boltzmann Machines	Exudates	Sensitivity=0.99 Accuracy=97.6%.
Hamad, H et al. [14]	DIARETDB0/1, IDRID, and e - optha	Mathematical morphology and FCM	Exudates	Sensitivity=83.3%, Specificity=99.2%, Accuracy =99.1%.

7. Conclusion

In this paper, we have presented an approach for the automatic detection of Diabetic Retinopathy (DR) using different deep - learning approaches. Our review paper's primary objective is to present multiple approaches for automatically detecting DR using deep learning and image processing algorithms. The study covers the essential details of fundus images for DR detection and classification, several methods for lesion detection and segmentation, and approaches for segmenting the retinal blood vessels. DR detection will be quicker and more accurate with the use of deep learning algorithms.

Acknowledgement I thank Sri Siddhartha Institute of Technology for encouraging me to do this work.

References

[1] Tajbakhsh N, Shin JY, Gurudu SR, Hurst RT, Kendall CB, Gotway MB, Jianming Liang. Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning? IEEE Trans Med Imaging.2016 May; 35 (5): 1299 - 1312. doi: 10.1109/TMI.2016.2535302. Epub 2016 Mar 7. PMID: 26978662.

[2] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3431–3440, 2015.

[3] Li Z, Jia M, Yang X, Xu M. Blood Vessel Segmentation of Retinal Image Based on Dense - U - Net Network. Micromachines (Basel).2021 Nov 29; 12 (12): 1478. doi: 10.3390/mi12121478. PMID: 34945328; PMCID: PMC8705734.

[4] Jiang Z, Zhang H, Wang Y, Ko SB. Retinal blood vessel segmentation using fully convolutional network with transfer learning. Comput Med Imaging Graph.2018 Sep; 68: 1 - 15. doi: 10.1016/j. compmedimag.2018.04.005. Epub 2018 Apr 26. PMID: 29775951.

[5] Pawe l Liskowski and Krzysztof Krawiec. Segmenting retinal blood vessels with deep neural networks. IEEE transactions on medical imaging, 35 (11): 2369–2380, 2016.

[6] Mateen, M.; Malik, T. S.; Hayat, S.; Hameed, M.; Sun, S.; Wen, J. Deep Learning Approach for Automatic Microaneurysms Detection. Sensors 2022, 22, 542. https: //doi. org/10.3390/s22020542.

[7] Long, S., Chen, J., Hu, A. et al. Microaneurysms detection in color fundus images using machine learning based on directional local contrast. BioMed Eng OnLine 19, 21 (2020). https: //doi. org/10.1186/s12938 - 020 - 00766 - 3.

[8] Islam, Sheikh & Hasan, Md Mahedi & Abdullah, Sohaib. (2020). Deep CNN - based early detection and grading of diabetic retinopathy using retinal fundus images.10.1201/9781003031352 - 6.

[9] Maqsood S, Damaševičius R, Maskeliūnas R. Hemorrhage Detection Based on 3D CNN Deep Learning Framework and Feature Fusion for Evaluating Retinal Abnormality in Diabetic Patients. Sensors (Basel).2021 Jun 3; 21 (11): 3865. doi: 10.3390/s21113865. PMID: 34205120; PMCID: PMC8199947.

[10] Aziz, T.; Ilesanmi, A. E.; Charoenlarpnopparut, C. Efficient and Accurate Hemorrhages Detection in Retinal Fundus Images Using Smart Window Features. Appl. Sci.2021, 11, 6391. https: //doi. org/10.3390/app11146391.

[11] Skouta, A., Elmoufidi, A., Jai - Andaloussi, S. et al. Hemorrhage semantic segmentation in fundus images for the diagnosis of diabetic retinopathy by using a convolutional neural network. J Big Data 9, 78 (2022). https: //doi. org/10.1186/s40537 - 022 - 00632 - 0.

[12] Wilver Auccahuasi, Edward Flores, Fernando Sernaque, Juanita Cueva, Monica Diaz, Elizabeth Oré, "Recognition of hard exudates using Deep Learning, Procedia Computer Science", Volume 167, 2020, Pages 2343 - 2353, ISSN 1877 - 0509, https: //doi. org/10.1016/j. procs.2020.03.287.

[13] Parham Khojasteh, Leandro Aparecido Passos Júnior, Tiago Carvalho, Edmar Rezende, Behzad Aliahmad, João Paulo Papa, Dinesh Kant Kumar, Exudate detection in fundus images using deeply - learnable features, Computers in Biology and Medicine, Volume 104, 2019, Pages 62 - 69, ISSN 0010 - 4825, https: //doi. org/10.1016/j. compbiomed.2018.10.031.

[14] Hamad, H.; Dwickat, T.; Tegolo, D.; Valenti, C. Exudates as Landmarks Identified through FCM Clustering in Retinal Images. Appl. Sci.2021, 11, 142. https: //doi. org/10.3390/app11010142.