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Machine Learning Techniques used for Recognizing the Diabetic Retinopathy: A Survey

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ABSTRACT
Diabetic Retinopathy (DR) is one of the major causes of blindness. DR mutilates the retinal blood vessels of a patient having diabetes. The DR has two major types: First one is Non- Proliferative Diabetic Retinopathy (NPDR) and second is Proliferative Diabetic Retinopathy (PDR). PDR is the advanced stage of DR which leads to neo vascularization, it is expected that the number of DR patients is to increase from 382 million to 592 million by 2028. In the early stages of the DR the patients were asymptomatic but in advanced stages, it leads to floaters, blurred vision, distortions, and progressive visual acuity loss. It is difficult but utmost important to detect the DR in early stages to avoid the worse effect of latter stages. The colour fundus images were used for the diagnosis of DR, the manual analysis could only be done by highly trained domain experts but it is bit expensive in terms of time and cost. Hence, it is important to use computer vision methods to automatically analyse the fundus images of Retina and assist the physicians/radiologists. The computer vision-based methods are divided into hand-on engineering and end-to-end learning. The hand-on engineering methods extract features using traditional approaches such as HoG, SIFT, LBP, Gabor filters, which failed to encode the variations in scale, rotation, and illumination. The end-to-end leaning automatically learns the hidden rich features and thus performs better classification.
Keywords— Diabetic Retinopathy (DR), Non- Proliferative Diabetic Retinopathy (NPDR), Proliferative Diabetic Retinopathy (PDR), HoG, SIFT, LBP, Gabor Filters.

I. Introduction

Diabetic Retinopathy (DR) was one of the major causes of blindness. DR mutilates the retinal blood vessels of a patient having diabetes. The DR had two major types: the Non- Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [9]. The DR in the early stages was called NPDR which was further divided into Mild, Moderate, and Severe stages. Where the mild stage has one Microaneurysma(MA), which is a small circular red dot at the end of blood vessels. In the Moderate stage the MAs rapture intodeeper layers and form a flame-shaped hemorrhage in the retina. The severe stage contains more than 20 intraretinal hemorrhages in each of the four quadrants, having definite venous bleeding with prominent intraretinal micro vascular abnormalities [10]. PDR was the advanced stage of DR which leads to neovascularization, a natural formation of new blood vessels in the form of functional microvascular networks that grow on the inside surface of the retina [11]. Globally, the number of DR patients was expected to increase from 382 million to 592 million by 2025 [12].
In the early stages of the DR the patients were asymptomatic but in advanced stages, it leads to floaters,blurred vision,distortions, and progressive visual acuity loss[13]. Hence, it was difficult but utmost important to detect the DR in early stages to avoid the worse effect of latter stages. As

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explained in the previous section, the color fundus images were used for the diagnosis of DR. The manual analysis could only be done by highly trained domain experts but expensive in terms of time and cost[14]. Therefore, it was important to use computer vision methods to automatically analyze the fundus images and assist the physicians/radiologists. The computer vision-based methods were divided into hand-on engineering [15] and end-to-end learning. The hand-on engineering methods extractfeatures using traditional approaches such as HoG, SIFT, LBP, Gabor filters and etc which failedto encode the variations in scale, rotation, and illumination. The end-to-end leaning automatically learns the hidden rich features and thus performs better classification [16]. Many hand-on engineering and end-to-end learning-based approaches were used to detect the DR in Kaggle dataset but no approach was able to detect the Mild stage. The detection of the mild stage was important for the early control of this fatal disease [17]. This study focuses to detect all the stages of DR (including the mild stage) using end-to-end deep ensemble networks. The results show that the proposed approachoutperforms state-of-the-art methods [18].
In order to get the finest mass image dataset to train models, it takes preprocessing steps, like data augmentation will increase the number of training examples, and data normalization will denoise to precisely predict classification [19]. So, they could train the latest CNNs model (AlexNet, VggNet, GoogleNet and ResNet) to recognize the slight differences between the image classes for DR Detection.Transfer learning and hyper-parameter tuning are adopted and the experimental results have demonstrated the better accuracy than non-transferring learning methodology on DR image classification[20].In the recent studies, several intelligence methods have been proposed by the researchers to detect DR as well as to get preclusion for progressive damage.MAs turnoverwas a noninvasive early detection method for analysis of DR have been described in [21] with a high accuracy, where two different approaches took place under the proposed methodology to diagnose the progression of DR [22]. A variety of attempts has been made to produce algorithms toautomatically classify and track micro-aneurysmal in the ocular fundus to resolve this variability [23]. DCNN a deep learning branch has impressive data on image analysis and interpretation applications,including medical imaging [24].Currently, large CNNs can successfullyperform highly complex image recognition tasks with an outstanding norm for many object classes [26].

II. Related works

In 2018, Wan *et al.*[1] have demonstrated DR was a common complication of diabetes and one of the majorcauses of blindness in the active population. Many of the complications of DR could be prevented by blood glucose control and timely treatment. Since the varieties and thecomplexities of DR,it was really difficult for DR detection in the time-consuming manual diagnosis. The attempt towards finding an automatic way to classify a given set of fundus image they brought CNNs power to DR detection, whichincluded 3 major difficult challenges: classification, segmentation and detection. Coupled with transfer learning and hyper-parameter tuning, it adoptedAlexNet, VggNet, GoogleNet,ResNet, and analyze how well these models do with the DR image classification. They employed publicly available Kaggle platform for training these models. The best classification accuracy was good and the results have demonstrated the better accuracy of CNNs and transfer learning on DR image classification.
In 2020, Rajan*et al*., [2] has implementeda state-of-the-artdeep learning models based on CNN, to exploit data-driven machine learning methods for the early prediction of DR. They framed the problem as a binary classification for the detection of DR of any grade(Grade 1–4) vs No-DR (Grade 0). They used 56,839 fundus images from the EyePACS dataset for training themodels. The models were tested on a test set from EyePACS (14,210 images), benchmark testdatasets Messidor-2(1748 images) and Messidor-1 (1200 images). They also discussed the challenges of automatedailment detection in medical images using CNNs, such as the use of public datasets for training, pre-processingmethods, performance metrics for unbalanced classes and present our results and their comparison with leading studies. The developed preliminary automated screening system will act as an aid to the manual diagnosticprocess by referring DR patients to an

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ophthalmologist for further examination (if detected positive) well in timeto reduce the risks of vision loss.

In 2020, L. Qiao *et al*., [3] have stated that rapid improvement of deep learning makes it gradually become an efficient technique to provide an interesting solution for medical image analysis problems. The proposed system analysis the presence of microaneurysm in fundus image using CNN algorithms that embedded deep learning as a core component accelerated with GPU(Graphics Processing Unit) which would perform medical image detection and segmentation with high-performance and low-latency inference. The semantic segmentation algorithm was utilized to classify the fundus picture as normal or infected. Semantic segmentation divided image pixels based on their common semantic to identify the feature of microaneurysm. It provided an automated system that would assist ophthalmologists to grade the fundus images as early NPDR, moderate NPDR, and severe NPDR. The Prognosis of Microaneurysm and early diagnosis system for non - proliferative diabetic retinopathy system had been proposed that was capable to train effectively a DCNN for semantic segmentation of fundus images which could increase the efficiency and accuracy of NPDR.

In 2019, Khan*et al.*[4] have proposed a DR detection system with the usage of the deep learning structure. DR causes impaired vision and mighteven lead to blindness if it was not diagnosed in early stages. DR hadfive stages or classes, namely normal, mild, moderate, severe and PDR.Normally, highly trained experts examine the colored fundus images to diagnose this fatal disease. This manual diagnosis of this condition (by clinicians) was tedious and error-prone.

Therefore, various computervision-based techniques have been proposed to automatically detect DR and its different stages from retina images. However, these methods were unable to encode the underlying complicated features and could only classify DR’s different stages with very low accuracy particularly, for the early stages. Here they used the publicly available Kaggle dataset of retina images to train an ensemble of five deep CNN models (Resnet50, Inceptionv3, Xception, Dense121, and Dense169) to encode the rich features and improve the classification for different stages of DR. The experimental results showed that theproposed model detected all the stages of DR unlike the current methods and performed better compared to state-of-the-art methods on the same Kaggle dataset.

In 2017,Jiang and Ming[5] have described a hierarchical multi-task deep learning framework for simultaneous diagnosis of DR severity and DR related features in fundus images. A hierarchical structure was introduced to incorporate the casual relationship between DR related features and DR severity levels.The proposed approach was evaluated ontwo independent testingsets using quadratic weighted Cohen’skappa coefficient, receiver operating characteristic analysis, and precision-recall analysis. A grader study was also conducted tocompare the performance of the proposed approach with those of general ophthalmologists with different levels of experience. The results demonstrated that the proposed approach could improve the performance for both DR severity diagnosis and DR related feature detection when comparing with the traditional deep learning-based methods.

In 2019,Deva *et al.*[6] have classified that DR occurs due to Type-II diabetes. It causes damages to the retinal bloodvessels and reason for visual impairment. The predicted center was around the probability ofvariation in the estimation of retinal veins, and the crisp enrolled vessel development inside theretina. To witness the changes segmentation of retinal blood vessels had to be made. To upgrade the quality of the segmentation results over morbid retinal images was proposed. Thisframework utilizes Contrast Limited Adaptive Histogram Equalization (CLAHE) for eliminating the background from the source image and enhanced the foreground blood vessel pixels, Tandem Pulse Coupled Neural Network (TPCNN) model was endorsed for automatic feature vectors generation, and Deep Learning Based Support Vector Machine (DLBSVM) was proposed for classification and extraction of blood vessels. The DLBSVM parameters are fine-tuned via Firefly algorithm. The STARE, DRIVE, HRF, REVIEW, and DRIONS fundus image datasets are deliberated to assess the recommended techniques.

In 2021,Kumar*et al.*[7] distinguished the stages and severity of DR to recommend needed medical attention.They presented DRISTI (Diabetic Retinopathy classification by analyzingretinal Images), where a hybrid deep learning model composed of VGG16 and capsule network was proposed, which yielded statistically significant performance improvement over thestate of the art. To validate the claim, they have reported detailed experimental and ablation studies. They have also created an augmented dataset to increase the APTOS dataset's size and check how robust the model was.The training and validation were good, respectively. They have also performed cross-dataset and mixed dataset testing to demonstrate the efficiency of DRISTI.

In 2019,Swetapadma*et al.*[8]have proposeda supervised learning-based approach using Artificial Neural Network (ANN) to achieve more accurate diagnoses outcomes for the case of DR. Features extracted from the retina images were used as an input to the ANN based classifier. Customized ANN architecture by estimating several entities of traditional ANN have been used to improve the accuracy of the method. The ANN architecture used in this work was feed forward back propagation neural network. Accuracy obtained for the proposed method was found to be good. The results suggest that proposed method can be used to detect diabetic retinopathy effectively.

III. Problem Definition

Blindness was the major disability in alive, where as one of the major causes of blindnessis DR.The implementation cost of the DR detection schemes is higher and the execution time is also high. Therefore, deep learning-based techniques are developed for solving these challenges. CNN [1] adoptsAlexNet, VggNet, GoogleNet,ResNetfor DR image classification. In this method, the accuracy of VggNet-s model was good compared to other models, the variability in morphological and other image features such as appearance, color, texture, was improved for identifying true haemorrhages of candidates.But, it has provides poor performance in terms of less classification accuracyand the lack of fundus image defects the data normalization and augmentation. CNN [2], reduces the risks of vision loss, In addition this process is very economical and time consuming.The labels used in this training and validation set were not adjudicated by any human experts and lacked interpretability. DCNN [3], performs medical image detection and segmentation with high performance with low latency interference.Moreover, it uses a semantic segmentation of fundus images, which could increase the efficiency and accuracy of NPDR.Hence, it takes more time for training and it causes lot of imbalances and the complexity of the developed model is high. CNN [4] has the capability to detect all the stages of DR with high detection accuracy andprovides higher specificity and sensitivity.But it needs trained experts for decision making on the final stage.Hierarchical multi- task learning [5] achieves more accurate results in both DR severity diagnosis and DR related feature detection.But it fails to encode the variations in scale, rotation, and illumination. DLSBVM [6]uses numerous layers and hence, it decreases the errors in misclassifying the vesselpixels from non-vessel pixels. In addition, it improves the contrast of the image and removes the noise from the images captured at different illuminations. Yet, the disparity in the image intensity between vessel and background causes the optimum blood vessels got neglected because of the nonappearance of the edges. DRISTI [7]gives higher convergence rate, which could potentially boost the DR patients' screening rate. But, the implementation cost of the system was very high and the dataset they used for this experiment was unbalanced for the distribution of classes. CNN [8] was designed using back-propagation neural network architecture and a weakly supervised learning method which gave some benefit over automatic DR detection.Since, it uses several filter techniques and network parameters hence the maintenance cost was high. These challenges are overcome by the newly developed retinopathy detection approach.

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Table 1: Features and challenges of existing deep learning methodologies to diagnose DR

Author [citation]	Methodology	Features	Challenges
Wan *et al.*, [1]	CNN	• The accuracy of VggNet-s model is good compared to other models. • The variability in morphological and other imagefeatures such as	• It has provided poor performance in terms of less classificationaccuracy. • The lack of fundus image defects data
		appearance, colour, texture,was improved for identifying true haemorrhage of candidates. .	normalization and augmentation.
Rajan, Paraye, *et al.*, [2]	CNN	• It reduces the risks of vision loss. • This process is timeconsuming andeconomical.	• It had a lack of interpretability. • The labels used in this training and validation set were not adjudicated by any human experts.
L. Qiao, Y. Zhu*et al.*,[3]	DCNN	• It uses a DCNN for semantic segmentation of fundus images which could increase the efficiency and accuracy of NPDR. • It performs medical image detection and segmentation with high -performance and low - latency interference.	• It takes more time for trainingand it causes lot of imbalance. • The complexity of the developed model ishigh.

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Khan, Gul Khan,*et al.*,[4]	CNN	• It has the capability to detect all the stages of DR with high detection accuracy. • It provides higher specificity and sensitivity.	• It needs trained experts for decision making on the final stage.
Jiang, and Ming, [5]	Hierarchical Multi-task learning.	• Its performance could achieve more accurate results in both DR severity diagnosis and DR related	• It fails to encode the variations in scale, rotation, and illumination.
		feature detection.	
Deva durai*et al.*,[6]	DLSBVM	• It improves the contrast of the image and removes the noise from the images captured at differentillumiinations. • It uses numerous layers and decreases the errors in misclassifying the vessel pixels from non-vesselpixels.	• The disparity in the image intensity between vessel and background causes the optimum blood vessels get neglected because ofthe nonappearance of the edges.
Chattopadhyay, Kumar, *etal.*,[7]	DRISTI	• The convergence rate of the model is high and could potentially boost the DR patients' screening rate.	• The dataset that they used for this experiment was unbalanced for the distributionof classes. • The implementation cost of the system is very high.

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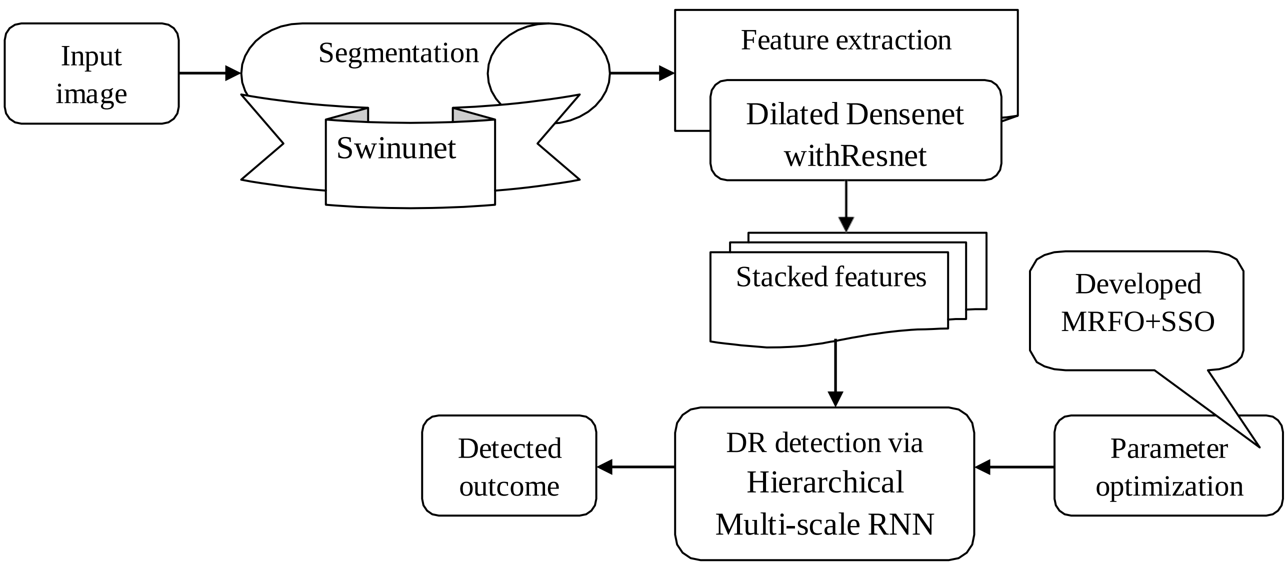
Swetapadma,Kumari, *et al.*, [8]	CNN	• It is designed using back-propagation neural network architecture. • It is a kind of a weakly supervised learning method which gave some benefit over automatic DR detection.	• It uses several filter techniques and network parameters. • The effectiveness of the method may decrease, if the images were not correctly obtained with accurate features.

IV. Research Methodology

Diabetic Retinopathy (DR) is a common complication of diabetes mellitus, which causeslesions on the retina that effect vision. If it is not detected early, it can lead to blindness. Unfortunately, DR is not a reversible process, and treatment only sustains vision. DR early detection and treatment can significantly reduce the risk of vision loss. The manual diagnosis process of DR retina fundus images by ophthalmologists is time, effort, and cost-consuming and prone to misdiagnosis unlike computer-aided diagnosis systems. Recently, deep learning has become one of the most common techniques that have achieved better performance in many areas, especially in medical image analysis and classification**.**Hence, we aimed to develop a DR detection approach with the adoption of deep learning structure in the segmentation phase and the detection phase. Initially, the required images for the detection of DR will be collected from the standard online data sources. Then, the collected image will be given for blood vessel segmentation using the Swinunet-based segmentation. For instance, the segmented images will be given to the Dilated-Densenetwith Resnet for the extraction of stacked features. The final stage detection will be carried out with the help of Hierarchical Multi-scale RNN with parameter optimization to give promising results over DR detection. The newly developed Manta Ray Foraging Optimization (MRFO) and Shark Smell Optimization (SSO) algorithm will be used here for maximizing the effectiveness of the developed DR detection approach. The implementation outcome will be analyzed over various DR detection approaches for validating the performance of the developed model. The architectural representation of the developed deep learning-based DR detection approach is shown in below Figure 1

Figure 1: Structural representation of the newly developed DR detection model



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V. Expected Outcome

The proposed model will be evaluated in Python and the performance analysis will be carried out. Here, Type I measures are positive measures like Accuracy, Sensitivity, Specificity, Precision, Negative Predictive Value (NPV), F1Score and Mathews Correlation Coefficient (MCC), and Type II measures are negative measures like False Positive Rate (FPR), False Negative Rate (FNR), and False Discovery Rate (FDR) were considered for the performance evaluation.

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