JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

ADVANCEMENTS IN MACHINE LEARNING TECHNIQUES FOR EARLY DIAGNOSIS OF DIABETIC RETINOPATHY

[1]Akshay Chobhe, [2]Ashish Bagate, [3]Indraneel Sarode, [4]Shubham Shewale, [5]Prof. Dipalee Rane

[1,2,3,4] B.E., Student, [5]Prof. of Department of Computer Engineering, Akurdi, Pune, Maharashtra, India.
[1]Department of Computer Engineering,
[1]D. Y. Patil College of Engineering, Akurdi, Pune, Maharashtra, India

Abstract : Diabetic retinopathy, a cause of vision loss requires early and accurate detection. This study introduces a method, for detecting retinopathy using machine learning techniques. We utilize Support Vector Machines (SVM) Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to ensure classification. The system analyzes features from high resolution fundus images to enable grading. By combining SVM, CNN and RNN strengths our approach outperforms methods, offering a path for improved diabetic retinopathy diagnosis. Our models experimental results demonstrate accuracy and consistency in identifying stages of DR(Diabetic Retinopathy). This research contributes to advancing automated diagnosis with the goal of impacting the timely treatment of diabetic retinopathy and preserving vision. Experiments on the Messidor dataset confirm the effectiveness of our proposed model, in grading DR.

IndexTerms **- Diabetic Retinopathy, Machine Learning, Support Vector Machines, Convolutional Neural Networks, Recurrent Neural Networks, Disease Classification, Integrated Approach.**

I. INTRODUCTION

Diabetic Retinopathy is a retinal complication that affects the retina in humans and can become progressive if not treated properly. Retinal diseases that cause the swelling and damageof blood vessels can cause blindness; during the early stages;small vessels may swell or rupture. It becomes very importantto diagnose the ailment in its preliminary stages becauseby the time its symptoms are apparent, one may already lose eyesight irreversibly due to the condition. The currentdiagnostics which includes resorting to manual inspection by an ophthalmologist is cumbersome, and may not be very useful, particularly in developing nations where physicians are scarce.Diabetic retinopathy was estimated to having caused about 5 percent of the global blindness in 2002 and hence the need tohave efficient diagnosis techniques. This means that, countrieswith increasing numbers of diabetic patients, especially in rural setting lack the necessary skilled human resource to deal with the problem. Diabetic Retinopathy is classified into five categories: Normal DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR. Severe DR, involves the blockage of blood vessels due to their swelling, thereby affecting blood flow. Proliferative DR is the most advanced level for DR which involves the development of new, fragile blood vessels in the retina, and can possibly contain blood in the vitreous chamber.The fragile new blood vessels formed in Proliferative DR can easily tear when they start to proliferate, which would cause blindness.

Considering the necessity for a well-defined and feasible diagnostic framework, this paper aims at a discussion of the utilization of machine learning methods, including Support Vector Machines, Convolutional Neural Networks, and Recurrent Neural Networks. Incorporating these higher level technologies, we will be positioning ourselves to improve the detection of Diabetic Retinopathy, in offering a relevant and effective means for early diagnosis and prevention. Additionally, the subsequent sections comprise of methodology, experiments, and results, which also reveals the possibility of this approach to revolutionize diabetic retinopathy diagnosis to drive the fight against avoidable blindness in the world.

II. RELATED WORKS

Researchers have been working on methodologies to automate the process of diabetic retinopathy detection. Here are some citations relevant to our paper in the field of diabetic retinopathy detection.

Enrique Carrera et al[1] proposed a method that is based on SVM to identify diabetic retinopathy in advance. This method involves an initial pre-processing stage in which the blood vessels, microneurysms and hard exudates are segregated and features are extracted that is used with SVM. The model tested resulted in a accuracy of 92.4 percent.
Accuracy: **92.4 %**

The method proposed by Shital N. Firke et al[2] introduces the Convolutional Neural Network for Diabetic Retinopathy Detection. For this method, Apatos Blindness Detection database is used to train the convolution neural network. Processing of

images in this method is done by resizing, pixel rescaling and label encoder. In this approach 3789 color retinal images are used to train proposed model. Also 948 images are obtained to test the model's efficiency inclassification.
Accuracy: **96.15 %**

Harry Pratt et al[3] proposed a method in their paper based on CNN for diabetic retinopathy detection. In this method, a dataset of 80,000 retinal images are used. These retinal images are rescaled into 512x512 pixels. The datasetis available on Kaggle. To define dynamic characteristics, the CNN architecture is built that is responsible for the task of classification.
Accuracy: **75 %**

Dinial Utami Nurul Qomariah et al[4] proposed a method based on deep learning for extraction and classification of features using Support Vector Machine algorithm. This method uses high level features of the last fully connected layer that is based on transfer learning mechanism. Thesefeatures from Convolutional Neural Network are input featuresfor classification using Support Vector Machine algorithm. This model evaluated on a diverse dataset, achieved a balanced accuracy of 92.3 percent, showcasing the efficiency of integrating traditional feature-based methods with deep learning.
Accuracy: **95.24 %**

Wei Zhang et al[5] proposed an automated method for diabetic retinopathy identification. It involves grading system called DeepDR. DeepDR is responsible for directly detecting the presence of diabetic retinopathy from fundus images. It also detects the severity of diabetic retinopathy using transfer learning and ensemble learning techniques. The model consists of neural networks which are based on combinationof well-known convolutional neural networks and deep neural networks.
Accuracy: **94.79 %**

Taken together, these studies highlight the shifting nature of the academic context of DR and its stages and training fellow ophthalmologists on how to identify the stages of diabetic retinopathy techniques including hybrids, the sequential anal- ysis of data, of implementing these concepts. In the following sections of our research, we synthesize information from this model that seeks to cohesively design a proper and efficient model. As a result, there is a need for an efficient application and assessment mechanism for diagnosing and categorizing diabetic retinopathy.

III. PROPOSED METHODOLOGY

3.1Dataset

The proposed model is evaluated on dataset that is publicly available. The messidor-2 data set (https://www.kaggle.com/datasets/andreivann17/messidor-2), which contains approximately 1800 fundus images. The ratio of retinal images that has pupil dilation to the retinal images that doesn't have pupil dilation is 2:1. The dimension of the fundus image is 1440 × 960, 2240 × 1488, or 2304× 1536;. According to the number of microaneurysms, hemorrhages, and the existence of neovascularization, each image is classified as one of five grades (Mild, Moderate, Normal, Proliferative and Severe).

3.2Pre-processing

In a comparison of the existing methods of detecting diabetic retinopathy using machine learning, the preprocessing can be defined as a set of activities, which are essential for the further process to train a deep learning model. The first step involves loading the labeled dataset, which is a process of loading the input data that you are going to use to train your model including the retinal images of patients with diabetic retinopathy and their classification according to their severity annotations. This data is noisy, hence multiple preprocessing is applied to it to reduce the amount of noise present in the data. To achieve this, the following steps were applied withan aim of ensuring that all images were in a format that canbe easily accessed by the users for training. Preprocessing involve cropping and scaling down of images. Cropping is performed in order to obtain the central retinal image. The pre-processing of images involves normalization with the help of z-score and min-max scaling methods. The images are readyto be given as input into the model. For feature extraction, a deep learning model, Convolutional Neural Network (CNN) is adopted. The last layer of classification is bypassed, and the features from the remaining layers are passed to the next layersto be classified. Other modifications are applied on top of the pre-trained model which is more suitable for the classification of diabetic retinopathy images and generally includes fully connected layers. The above data set is preprocessed and the model is trained with it, and the accuracy and loss rates are checked during the training process. Some of the preprocessing steps may be applied universally, while others are selected depending on the properties of the dataset and potential requirements for the chosen machine learning algorithm.

3.3Model Training and Architecture

The models include Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Recurrent NeuralNetworks (RNN) and each of them is trained with the dataset specified as training data. This training process involvesthe repeated fine-tuning of weight parameters and other factors like the network's bias. The goal is to let the models detect fine details within the image of the retina and develop the capability for projecting pertinent aspects of Diabetic Retinopathy about the levels of severity.

To perform the task of diabetic retinopathy detection, we used Support Vector Machines (SVM), Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). They were developed to exploit features and patterns unique to retinal images that are typical in those algorithms.

1) Support Vector Machine (SVM): Support Vector Machine are used because they have shown promising results for the classification of the retinal images with different DR severity levels. SVM classification involves feature extraction and classification as indicated in the following. Following pre-processing the retinal images are features which characterize them, are converted into feature vectors. They may include the pixel intensity, texture features and shapes derived from the

cropped and resized images. SVM then finds a hyperplane that best classifies the different severity classes of the feature space. In this testing phase, the retinal images which are unseen by the system are pre-processed and then transformed into a feature vector before being fed into the trained SVM model. SVM then separates the images into the defined degree of severity based on the decision boundary it has trained.

2) Convolutional Neural Networks (CNN): CNNs are used in learning spatial hierarchies and local structures in the retinal image. The CNN architecture consists of the convolutional layers which are the initial layers which take in the convolution operation, applying filters to the image to obtain the local features and patterns. The convolutional layers learn hierarchical representations in which the network detects low-level features (e.g. terminal nodes and edges) to early layers and high-level features, (e.g. complex structures) in deeper layers while keeping simpler structures in layers closer to the input/output interfaces. The pooling layers act to down-sample the features maps that are produced by the convolutional layers and retain only important information. Lastly, the fully connected layers are used to make features learn global relations and patterns from the previously extracted abstract features. The final fully connected layergenerates a probability distribution of each severity class using various activation functions.

3) Recurrent Neural Networks (RNN): Recurrent Neural Networks are utilized for managing temporal connections existing in sequential retinal images data. The architecture of RNN is of recurrent layers that enable the network to store memory of past information. In the context of applying the model to diabetic retinopathy detection, the periodic nature of the time series of retinal images taken over time is taken into account to identify temporal features and trends. Seeing that DR develops over a period of time, the RNN analyses sequential images of the retina and theirs features over time.

3.4Integration

To combine the strength of all the algorithms, the integration technique is applied at the decision level. The probabilities from SVM, CNN, and RNN are then averaged, and an ensemble learning technique is applied to give the final result. This ensures that the retinal image analysis is done usingspatial, temporal and global features hence increasing the levelof accuracy. The integration of all these different machine learning models is done with the goal of developing a strong and efficient model for diagnosing diabetic retinopathy.

3.5Model Evaluation

To assess the performance of the trained models, a comprehensive set of evaluation metrics are employed. These metrics include:

1. Accuracy: This is a metric that determines the extent of correctness of the models in as a capacity of determining the severity of diabetic retinopathy. It measures the extent to which the model has classified the testing data set. It measures overall correctness of the model.
   Accuracy = TP + TN / TP + FP + TN + FN
2. Precision: Precision assesses the values that were rightly predicted as positives and it measures the ability to prevent false negative predictions. Precision is always calculated as the ratio of true positive values to the sum of true positive values and false positive values.
   Precision = TP / TP + FP
3. Recall: Recall determines the models' performance in detecting all the positives out of the total positive cases. Recall is always measured as the ratio of true positive valuesto the sum of true positive values and false negative values.
   Recall = TP / TP + FN

The trained model is tested on the testing set using the abovementioned three metrics. In order to achieve the objectivesof the work, the assessment of the models' performance in accurately predicting the input retinal image based on theseverity levels of diabetic retinopathy is provided. As viewed, the higher the values of accuracy, precision and recall, the better the model, as they denote a reliable model. Accuracy and recall make a good positive pair together with F1 score, which, when summed up with precision, provide a complete picture of the models' performance. This approach is more suitable than focusing only on a single measure; it gives more insights about the capability of the model in performing well on unseen data and shows the ability of model to detect variouslevels of diabetic retinopathy.

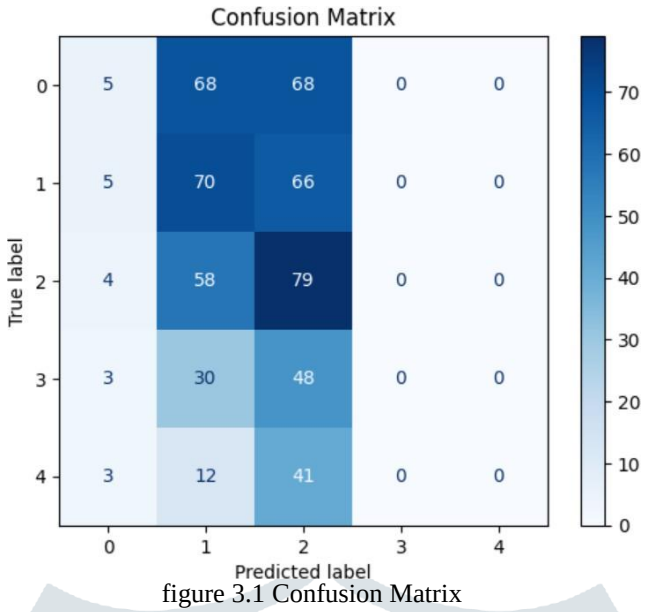

figure 3.1 Confusion Matrix

IV. EXPERIMENT RESULTS

The integration of machine learning models like CNN, RNN and SVM have been done to improve the overall efficiency as well as accuracy of the model. The accuracyof the model is dependent on various factors like number of convolutional layers used in CNN and RNN and the number of dropout samples. Integration of these machine learning models make the proposed model more robust and powerful. A result of the proposed model is provided in this section. Using evaluation metrics such as Accuracy, Precision and Recall, the results are as follows:

table 3.1 Results Obtained

Training Accuracy	Testing Accuracy	Loss
89.39%	88.12%	0.3299

V. IMPLEMENTATION DETAILS

a) No DR b) Mild DR c)Moderate DR d) Proliferative DR e) Severe DR

figure 5.1. Retinal Images for Diabetic Retinopathy with Disease Grades

VI. CONCLUSION

Most people suffer from diabetes which is the main cause ofdiabetic retinopathy. It can also lead to permanent blindness ifnot detected in early stages. Hence a model must be developedfor early diagnosis and detection of diabetic retinopathy. DeepLearning algorithms like CNN and RNN which work accurately for classification of images are employed. The proposed model is a combination of CNN, RNN and SVM. SVM is employed for effectively grading the retinal images into various classes based on severity levels. The messidor-2 data set is used for experiments. The experimental findings show that in terms of accuracy, sensitivity and other metrics the proposed model performs better than the other representative models. Based on the results, the proposed combination modelcan provide good results to build a robust diabetic retinopathy detection model.

VII. FUTURE SCOPE

The future scope of this model includes that the modelcan be trained on more datasets to be capable of detectinga lot more diseases. The proposed model can be integrated into existing healthcare systems for effective detection and prediction.

REFERENCES

[1] Kaggle Dataset: https://www.kaggle.com/datasets/andreivann17/ messidor-2

[2] S. Huang, J. Li, Y. Xiao, N. Shen and T. Xu, ”RTNet: Relation Trans- former Network for Diabetic Retinopathy MultiLesion Segmentation,” in IEEE Transactions on Medical Imaging, June 2022

[3] S. Thorat, A. Chavan, P. Sawant, S. Kulkarni, N. Sisodiya and A. Kolapkar, ”Diabetic Retinopathy Detection by means of Deep Learning,” 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2021

[4] S. Kumar and B. Kumar, ”Diabetic Retinopathy Detection by Extracting Area and Number of Microaneurysm from Colour Fundus Image,”2018 5th International Conference on Signal Processing and Integrated Net- works (SPIN), Noida, 2018, pp. 359-364.

[5] A Prospective Study on Diabetic Retinopathy Detection Based on Modify Convolutional Neural Network Using Fundus Images:https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9914220/#:~:text=To%20address%20this%20challenge%2C%20the, for%20the% 20prediction%20of%20DR.

[6] H. Greenspan, B. van Ginneken, and R. M. Summers, “Guest editorial deep learning in medical imaging: Overview and future promise of an exciting new technique,” IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1153–1159, May 2016.

[7] N. J. Mohan, R. Murugan, T. Goel and P. Roy, ”DRFL: Federated Learning in Diabetic Retinopathy Grading Using Fundus Images,” in IEEE Transactions on Parallel and Distributed Systems, June 2023

[8] Diabetic Retinopathy Diagnosis based on Convolutional Neural Network: https://iopscience.iop.org/article/10.1088/1742-6596/1999/ 1/012117/pdf

[9] L. Qiao, Y. Zhu and H. Zhou, ”Diabetic Retinopathy Detection Using Prognosis of Microaneurysm and Early Diagnosis System for Non- Proliferative Diabetic Retinopathy Based on Deep Learning Algorithms,” in IEEE Access, 2020

[10] S. Joshi, R. Kumar, P. K. Rai and S. Garg, ”Diabetic Retinopathy Using Deep Learning,” 2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), Greater Noida, India, 2023

[11] A. S. Mayya, ”Deep Learning for Early Diagnosis of Diabetic Retinopathy: a Study Using Convolutional Neural Network,” 2023 IV International Conference on Neural Networks and Neurotechnologies (NeuroNT), Saint Petersburg, Russian Federation, 2023

[12]Detection of Diabetic Retinopathy Using Bichannel Convolutional Neural Network: https://www.hindawi.com/journals/joph/2020/9139713/

[13] Ankita Gupta et al., “Diabetic Retinopathy: Present and Past” International Conference on Computational Intelligence and Data Science, pp. 1432-1440, 2018.

[14] Nikhil M N et al., “Diabetic Retinopathy Stage Classification using CNN” International Research Journal of Engineering and Technology, pp 5969-5974, 2019.

[15] Kele Xu et al., “Deep Convolutional Neural Network Based Early Automated Detection of Diabetic Retinopathy using Fundus Image”, Molecules, vol.22, no.12, pp.1-7, 2017.

[16]Optimized CNN Model for Diabetic Retinopathy Detection and Classification: https://ijisae.org/index.php/IJISAE/article/view/2957/1535

[17]S. Wang et al., ”Diabetic Retinopathy Diagnosis Using Multichannel Generative Adversarial Network With Semisupervision,” in IEEE Trans- actions on Automation Science and Engineering, April 2021.