

Survey of Diabetic Retinopathy Classification using Machine Learning

Vrishali Rajendra Kadam, Dr. B. D. Phulpagar

Computer Engineering Department, Savitribai Phule Pune University

P.E.S. Modern College of Engineering, Pune

vrishali.kadam@moderncoe.edu.in, bhagwan.phulpagar@moderncoe.edu.in

Abstract:

Diabetic Retinopathy (DR) is a disorder of the retina induced by long-term diabetes. As the condition advances, the vision becomes distorted and fuzzy. To diagnose DR using a color fundus image, trained doctors must first determine the presence of essential characteristics, which is a complex and time-consuming task. To diagnose DR using digital fundus images, we propose using a CNN (Convolutional Neural Network) technique. In our study, we used a novel method in which the entire image was segmented and only the regions of interest were used for subsequent processing. Not only does the suggested system detect DR, but it also assists the user in communicating with the appropriate doctor. This enables the user to solve their problem and receive an appropriate subscription for health-related difficulties.

Key Words: Convolutional neural network, Diabetic retinopathy (DR), Python, Django framework

I. INTRODUCTION

DR is one of the most common causes of blindness in persons with diabetes mellitus. When left undiscovered, ill-advised, and untreated for a long time, this disease is regarded as prevalent comorbidity created as an eventual consequent complication of diabetes mellitus. Visual impairment results from neovascularization caused by retinal detachment, hemorrhage, retinal capillary no perfusion, and macular edema. Time and resource usage for disease prediction for a large number of potential patients is critical in combating the horrors associated with this disease. Various machine learning algorithms are employed to predict and identify this disease, resulting in accurate patient diagnosis. However, none of the algorithmic solutions delivered adequate results. This prompted the development of a model that combines existing machine learning methodologies to obtain the best prediction outcomes from these algorithms. For classifying DR dataset, the current study employs an ensemble based machine learning model that combines the use of Random Forest classifier, Decision Tree classifier, Adaboost classifier, K- Nearest Neighbour classifier, and Logistic Regression classifier. The DR dataset is first normalized using the min- max normalization approach, and then the ensemble model is used to train it. Several performance criteria, such as specificity, sensitivity, and accuracy, are used to evaluate the suggested ensemble model. Finally, the suggested model is compared to the performance of the different ML algorithms.

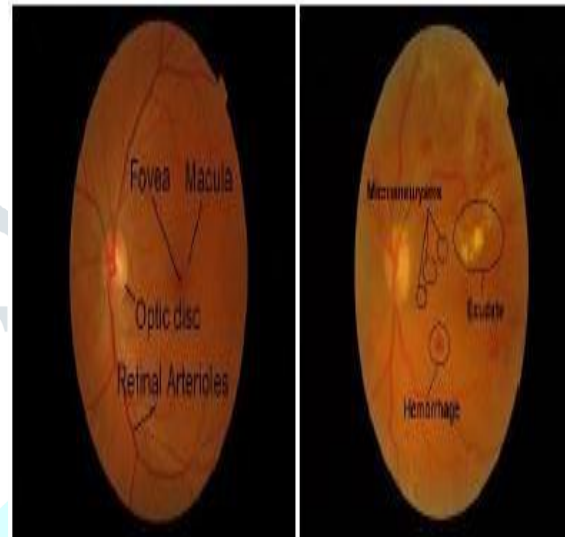


Figure 1: Example of a normal retina (left) and DR (right) (5)

Many scientists have worked to create an automatic Computer-Aided Detection (CAD) method for DR. Although different techniques have been presented [4,] HEM detection in retinal fundus imaging and its accuracy remain a major problem. The restrictions are mostly due to the eye's spherical shape, which results in a brighter region in the retina's center and dark patches at the edges. It is difficult to reliably diagnose HEM because to non-uniform lighting, low contrast, small lesions, and the existence of items in a normal retina that have similar characteristics as HEM [5] such as the optic disc, blood vessels, and so on. Tiny patches that can be lost during image processing define HEM.

II. LITERATURE SURVEY

G Thippa Reddy et.al [1] On the DR dataset, an ensemble based machine learning model consisting of the Machine Learning (ML) Algorithms Random Forest classifier, Decision Tree classifier, Adaboost classifier, K-Nearest Neighbour classifier, and Logistic Regression classifier is tested. The DR dataset is first normalized using the min-max normalization method.

Ajay S .Ladkat et.al [2] DR is an eye condition in which the patient's retina is harmed by an increase in insulin levels in the blood. The symptoms can cause the patient's eyesight to be distorted or blurred, resulting in blindness. We must first distinguish between exudate and no exudate pixels in order to detect exudates automatically.

Ajay S .Ladkat et.al [3] Each pixel must be processed separately for picture processing. This operation will take too long if carried out successively. As a result, parallel processing on all pixels is required to decrease the time. As a result, rather than working on each pixel individually, operations on all pixels are performed simultaneously. When compared to sequential processing, the speed of parallel processes is greatly boosted.

Mamta Arora et.al [4] DR is a medical condition induced by diabetes that results in retinal deterioration and blood leakage. If not treated promptly, this condition can cause a wide range of symptoms, from moderate vision problems to complete blindness. The results show that LESH is the highest performing strategy when using SVM with a Radial Basis Function kernel, with an accuracy of 0.904. Similarly, LESH with SVM-RBF has the best AUC performance, at 0.931.

Mohamed Chetoui et.al [5] DR is a medical disorder caused by diabetes mellitus that causes retinal degeneration and blood leakage. If not treated promptly, this illness can produce a variety of symptoms ranging from minor vision difficulties to full blindness. The experimental findings demonstrate that utilizing SVM with a Radial Basis Function kernel, LESH is the best performing approach, with an accuracy of 0.904. Similarly, the ROC curve study reveals that LESH with SVM-RBF has the best AUC (Area under Curve) performance, with 0.931.

Sahil Chelaramani et.al [6] while accurate disease prediction from retinal fundus pictures is important, gathering huge volumes of high-quality labeled training data to develop supervised algorithms is difficult. Deep learning classifiers have shown high-accuracy outcomes in a range of medical imaging situations, but they require a lot of labeled data.

G Thippa Reddy et.al [7] DR is a condition in which diabetes mellitus damages the retina. Currently, diagnosing DR is a time-consuming manual approach that necessitates the inspection and breakdown of fundus images by a clinical master. With the most efficient ML classification algorithm, this feature extraction technique could help automatic characterization of retina images for DR with an accuracy of 83%, allowing specialists to quickly recognize the patient's condition in progressively precise manner.

S M Asiful Huda et.al [8] Using a ML technique, this work detects the presence of DR in the human eye. The proposed method uses classification algorithms to classify numerous parameters of an existing DR dataset. The traits were then retrieved and used to make a final conclusion on whether or not DR was present. Decision Tree and Logistic Regression were used in the suggested system. For the prediction, we used a SVM.

Thippa Reddy Gadekallu et.al [9] DR is a common cause of blindness in the elderly and has grown into a global medical problem in recent decades. There are various scientific and medical ways to screening and detecting this condition, but retinal fundus imaging is used the most. The DR dataset was first standardized using a standard scaler normalization approach, then dimensionality was reduced using PCA, then suitable hyper parameters were chosen using GWO, and

finally the dataset was trained using a DNN model. Accuracy, recall, sensitivity, and specificity are the performance measures used to evaluate the suggested model.

Mobeen-ur-Rehman et.al [10] Diabetes is a disease that is rapidly becoming a major threat to humanity, despite significant scientific and medical progress. Its only treatment is early discovery and preventative measures to minimize its consequences. Because it affects all body parts and organs, there are ways to detect its existence before it causes serious harm. For the classification of DR pictures, the paper employs a CNN technique. AlexNet, VGG-16, and Squeeze Net were utilized as pre-trained CNN models, with classification accuracy of 93.46 percent, 91.82 percent, and 94.49 percent, respectively.

Nikos Tsiknakis et.al [11] Diabetes mellitus causes DR, which is the primary cause of blindness worldwide. To postpone or avoid vision degradation and loss, early detection and treatment are required. To that purpose, various artificial intelligence-powered methods for detecting and classifying DR on fundus retina images have been proposed by the research community.

M. Mohsin Butt et.al [12] DR is one of the most common causes of blindness in diabetic people. DR has a variety of effects on the eye, all of which can lead to visual loss. Early identification of DR is critical for ophthalmologists to provide appropriate treatment. The main cause of DR is high blood sugar, which damages the blood vessels within the retinal tissues. This can occur as a result of inadequate insulin synthesis or insulin resistance in the cells.

San-Li Yi et.al [13] The early detection and grade diagnosis of DR are critical for avoiding blindness, and the use of deep learning approaches to automatically identify DR has piqued interest. However, the minimal amount of DR data available limits its use.

Gao Jinfeng et.al [14] DR is an eye disease caused by diabetes that destroys the eye's blood vessels. If not discovered early enough, DR can result in impaired vision or even blindness. DR is divided into five stages: normal, mild, moderate, severe, and PDR. Many hand-on computer vision initiatives have been used in the past to identify DR, but they are unable to code the subtle underlying features. As a result, inadequate classification of DR phases, particularly early stages, occurs.

Kang Zhou et.al [15] DR is a serious eye disease that affects people who have diabetes. A retinal image analysis technique for DR screening is in great demand. Because the retinal image resolution is so great, small problematic tissues can only be recognized with a high resolution image, and a large local receptive field is necessary to detect late-stage disease.

III. Existing System

A dataset is a collection of necessary data that is kept in a database. The described system utilized photographs as its dataset, resulting in the creation of a database. The larger the database, the more precise the result, and this database has 732 high-quality retina photos collected with fundus photography. Because categorical classification is utilized, the dataset is

divided into five categories: mild, moderate, severe, and proliferative (numbers 0, 1, 2,3,4). Each training dataset folder is labeled and contains high-resolution fundus photography photos of the human eye for neural network training.

Image processing, pattern recognition, and video recognition are just a few of the applications for CNN. In image classification, CNN takes an image as input and assigns it to the correct category. Convolution is used in a variety of hidden layers to extract features and other relevant information from the image. The classification layer generates the output. The image is segmented into multiple regions (or segments) in R-CNN, and the CNN is forced to focus on them. Due to the extraction of region of interest, object detection accuracy is much higher than that of CNN.

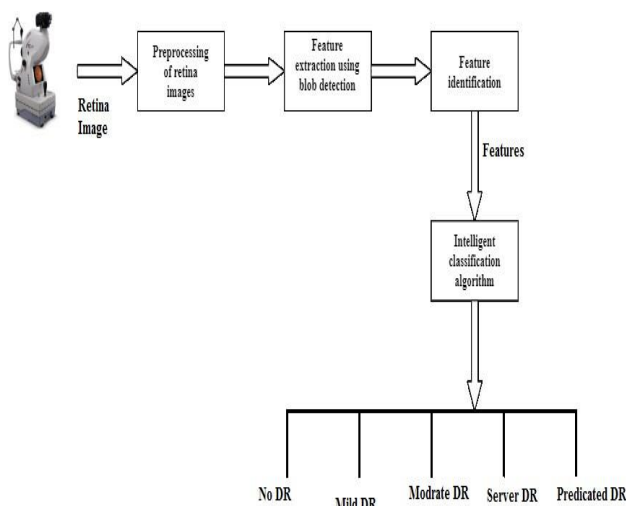


Figure 2: Existing System

The original fundus photos are scaled to 336 x 448 pixels at first. Preprocessing is required due to the vast amount of information and changing contrast of images collected from fundus cameras. Images without preprocessing suffer from vignetting and picture distortion. Because the photos were taken with separate fundus cameras, they will have varied levels of illumination; hence illumination normalization procedures must be used.

The number of neurons in the input layer is the same as the number of pixels in the input image. The convolutional layer uses convolutional features to calculate the product of the picture patches and the filter. ReLU (Rectified Linear Unit) can be utilized for the activation layer. The ReLU layer does a threshold operation to each input element, setting any value less than zero to zero. The output of the convolutional layer is activated element by element. The pooling layer's purpose is to down convert the volume in order to speed up the computation and reduce memory use. The information about the features, such as edges, contrast, blobs, and forms, is stored in the convolutional layer that comes before the fully connected layer. The information from the previous layers is

gathered in the fully linked layer. The final layer of CNN [9] is a softmax layer. Each class is given numerical probability. The output layer divides the input images into two categories: normal (no DR) and abnormal (DR) (with DR). The output of all the neurons from the previous layer is fed into the fully connected layer. The created layers are utilized for image training and testing. [10].

KNN

Nearest Neighbour (K) (KNN) KNN is a traditional ML technique that is commonly used to address classification and regression problems. The datasets are classified in KNN using the distance function's similarity measurement. It's a non-parametric supervised learning technique with a wide range of applications in data mining, image processing, intrusion detection, pattern recognition, and other fields. The majority of votes to the appropriate nearest Neighbour determines the classification of the data in KNN. In KNN, the number of neighbors is the most essential and major deciding factor in the classification process. In addition, the method employs all of the training data in the testing phase, obviating the necessity for distinct data points for the training model construction. In order to scan all available data points that require more storage, the time and expense factor increases. The KNN algorithm begins with the selection of the k closest data points, followed by classification of the points using the majority of votes for the k neighbors. For prediction, the class with the most votes from their objects is chosen. The distance between data points is calculated using the Euclidean distance; Hamming tone distance function, and Murkowski distance function. KNN's performance improves when the number of features is reduced. Over fitting occurs as the number of characteristics increases. [1].

Support Vector Machine

Support Another superior classification technique is Vector Machine, which primarily draws a boundary between two classes to distinguish between them. When the number of features is large, SVM beats regression models and neural networks [8]. In order to determine the classes in our problem, we used Linear SVC, which has an alternative multiclass technique.

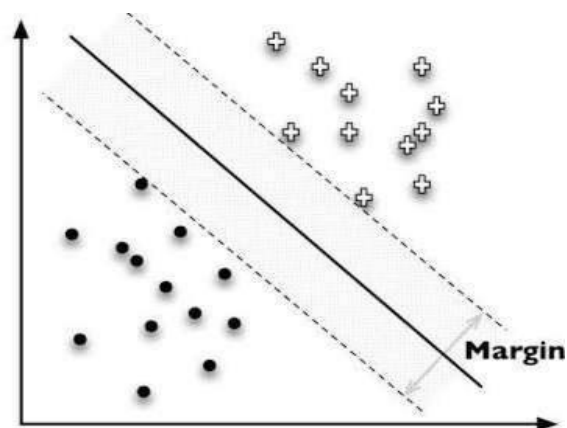


Figure 3: SVM (8)

CNN

In this paper, convolutional neural networks (CNN) are used. Convolution layers for feature extraction and neural networks for classification are the two main components. The initial and middle layers of CNN's convolution layer use specified kernels that are convolved with the image to detect required patterns, colors, or forms. The CNN's first layers are convolution layers, which extract observable features from an image. The CNN's next several layers use convolution with kernels to extract features that are more abstract and concealed from the output of the initial levels. To identify the image, the last layer uses neural networks to process the weighted influence of all the features. Although other CNN models exist, such as AlexNet, VGG-s, VggNet-vd-16, and VggNet-vd-19, these models are prone to the over fitting problem because to the complexity of the shapes and patterns. As a result, in this paper, CNN architecture is constructed from scratch to maximize DR identification utilizing fundus images.

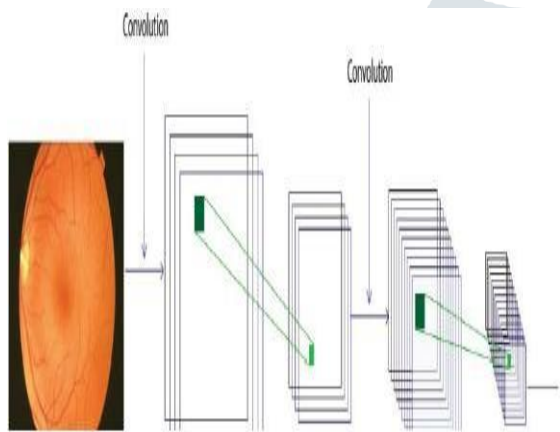


Figure 4: Implemented System Flow (10)

IV.CONCLUSION

Our research shown that ML approaches such as neural networks have a bright future in disease identification using medical imagery. The CNN technique has already been proven to be effective in the field of object detection. This research demonstrates that CNN can also be used to detect very small features. For lesion detection, CNN has been demonstrated to be extremely accurate and sensitive.

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