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A Survey paper on Diagnosis and Classification of Diabetic Retinopathy Using Machine Learning

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Abstract: Diabetic Retinopathy is human eye disease which causes damage to retina of eye and it may eventually lead to complete blindness. Detection of diabetic retinopathy in early stage is essential to avoid complete blindness. Many physical tests like visual acuity test, pupil dilation, optical coherence tomography can be used to detect diabetic retinopathy but they are very time consuming and costly.There are many features present in retina but the exudates feature which is one of the primary signs of diabetic retinopathy and which is a main cause of blindness that could be prevented with the help of this automatic detection process. In feature extraction Pupil dilation is important step in the normal screening process but this affects Diabetes vision. The automatic detection process reduces examination time, and increase accuracy. In this paper we provide review on many techniques and algorithms that helps to diagnose Diabetic Retinopathy in retinal fundus images. This paper also reviews, classifies and compares the algorithms and techniques previously proposed in order to develop better and more effective algorithms.
Keywords: Diabetic Retinopathy, Machine Learning, SVM ,Neural Networks , CNN ,KNN

I. INTRODUCTION

Diabetic Retinopathy (DR) is one of the widespread retinal problems of diabetic patients with long-lasting illnesses and the primary cause of blindness. Early diagnosis and continuous scanning are the effective treatment of diabetic retinopathy. Ophthalmologists require more time to monitor or diagnose the disease. If the disease is not detected at the proper time and correctly, it may lead to blindness in diabetic persons. To prevent vision loss, the automated detection of diabetic retinopathy is needed.

II. LITERATURE REVIEW

In [4] this paper authors used Fuzzy C-means clustering to segment the blood vessels in the image. After pre-processing of images is completed, features such as Radius, Diameter, Area, Arc length, Centre Angle and Half area are calculated for each image. Then Modelling Techniques like PNN, Bayes Theory and SVM areused and their performances are compared. Finally, the images are classified into three groups namely, normal image, Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). This paper infers that the SVM model outperforms all other models. Also,the system is run on 130 images available from “DIARETDB0: Evaluation Database and Methodology for Diabetic Retinopathy” and the results show that PNN has an accuracy of 87.69% Bayes Classifier has an accuracy of 90.76% and SVM has an accuracy of 95.38%.

In [2] this paper focuses on automated computer-aided detection of diabetic retinopathy (DR) using features drawn from output of different retinal image processing algorithms, like diameter of optic disk, lesion specific (microaneurysms, exudates), image level (pre-screening, AM/FM, quality assessment). These features are then used in an ensemble machine learning system comprising of different learning algorithms like alternating decision tree, adaBoost, Naïve Bayes, Random Forest and SVM.The characteristic features extracted by anatomical part recognition algorithms and lesion detection are used to classify images. This paper proposed methods to develop an automated system to detect the case of diabetic retinopathy among the diabetic patients and is aimed at helping ophthalmologists to detect early symptoms of diabetic retinopathy with ease. The ideas proposed for the intelligent system can be understood by this paper. Also, this paper highlights various technologies used for diagnosis and detection of diabetic eye disease.

In [3] this paper proposes a new computer assisted diagnosisbased on the digital processing of retinal images in order tohelp people detecting diabetic retinopathy in advance. Themain goal is to automatically classify the non-proliferativediabetic retinopathy grade of any retinal image. For that, an initial image processing stage isolates blood vessel, microaneurysms and hard exudates in order to extract features that can be used by a support vector machine (SVM) to figure out the retinopathy grade of each retinal image. The image database used in this study is the Messidor database.A decision tree classifier is also implemented to contrast the results obtained with our SVM classifier. The results are encouraging and a future clinical evaluation will integrate the presented algorithms in a tool for diagnosis of diabetic retinopathy. Other future works are the detection of soft exudates, besides hard exudates, and the application of texture analysis in order to improve accuracy and sensibility of the retinopathy detector.

In [4] this paper the work, authors want to detect if DR is present or not, only two classes will be considered. The database is labelled as normal for all the images with no DR and as abnormal for all the images with DR, no matter the grade of the retinopathy. In addition, since they are interested in extracting structural features using the retinal image fundus, they have converted the colour images to grayscale for further processing. After the image processing using LTP, two feature histograms are obtained for each image (upper and lower). Each histogram is normalized using a bin-width of 25. The results are two vectors of dimension 25 each. In this work, the best performing threshold was equal to 5. A similar histogram was extracted from the LBP image and can serve as a baseline for comparison with other LBP texture-based DR techniques. The proposed approach is suitable even for small datasets. New techniques based on deep learning are data hungry but show impressive performances in different classification tasks including DR. Future work includes benchmarking the performance of deep learning techniques and the proposed texture-based features in a small dataset such as MESSIDOR.

In [5] this paper proposes an automated diagnosis approach of Diabetic Retinopathy based on an immense and crucial feature extracted from the DIARET-DB dataset to help people detecting diabetic retinopathy at the primary level. The dataset contains 15945 samples along with 66 features associated with each samplereferring to various symptoms of a primary, mild and advanced level of Diabetic Retinopathy. Some of the features are Area, bounding box, convex area, Regional intensity coefficients corresponding to the max, min, mean variance of the green plane, red plane etc. By applying a feature selection technique, the most important and crucial features were extracted first. Then those features were used to train some of the superior machine learning models to figure out how accurate our model works in determining the presence of the symptoms on a patient’s eye. The main goal here is to automatically classify the proliferative as well as non-proliferative diabetic retinopathy grade of any retinal image.Therefore, this research proposed an automated method to diagnosing and detect early stages of diabetic retinopathy e.g., microaneurysms, exudates, cotton wool spots, etc. based on supervised machine learning algorithms. The proposed method also obtains a better result than existing approaches by introducing a tree-based feature selection method rather than irrelevant features-building of existing approaches

Proposed Methodology

In this paper we have considered CNN, SVM and KNN for the classification purpose. Here we are going to use the common feature extraction process for every classification, the feature extraction method to be used is that of the CNN classifier which will be common for all the algorithms. The classifiers will have the directly high-level featured images as input.

A CNN is first trained using raw images as input. The hidden layer feature maps of the trained CNN are then used to detect the object based on the detection result, we crop some image patches each of which tightly contains either the whole object or one object part.

These generated images are referred to as object-focused and part-focused images. As such, the original images are augmented by focusing on the targets at different levels.

Object Detection

A well-trained CNN should make good use of the patterns that are useful for distinguishing between different categories. Since the background is generally irrelevant to object categorization, the active regions usually reside within the object. Although some background regions may contain patterns similar to those in the object, the background patterns usually correspond to low-level features and the corresponding regions are unlikely to remain active in the higher-level feature maps.

Part Detection

The key component of our system is to automatically detect the object parts using the hidden layer features of the CNN trained with raw images and their class labels only. We first choose the feature maps which are likely to be activated by the object parts

Integration

After the object-focused and part-focused images are generated, we construct one more CNN initialized with that previously trained using the raw images for each part. We fine-tune the CNNs for the object parts using the corresponding part-focused images so the new CNNs are specialized to extract discriminative features from different parts.

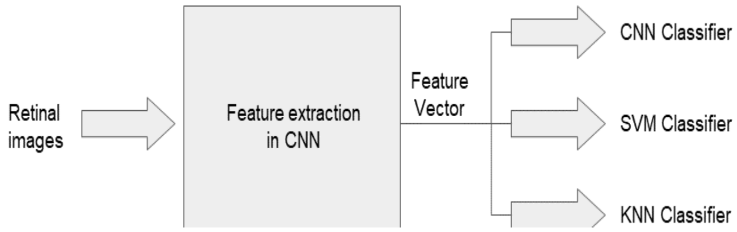

Fig. 1. Proposed system architecture

For ensemble selection, following energy functions are used:

- Sensitivity = $\frac{TP}{TP + FN}$

- Accuracy = $\frac{TP + TN}{TP + FP + TN + FN}$

- F-score = $\frac{2TP}{2TP + FN + FP}$

where TP, FP, TN, FN represent the true and false positive and true and false negative classifications of the system respectively.

Algorithms

CNN image classifications take an input image, process it and classify it under certain categories (E.g., Dog, Cat, Tiger, Lion). Computers see an input image as array of pixels and it depends on the image resolution. Based on the image resolution, it will see h x w x d(h = Height, w = Width, d = Dimension). E.g., An image of 6 x 6 x 3 array of matrix of RGB (3 refers to RGB values) and an image of 4 x 4 x 1 array of matrix of grayscale image.

Neural Network are the learning algorithm that mimic human brain. They are the classification algorithm that can classify an example into multiple classes. A multi-layer neural network will be used where the first layer is the input layer and the last layer is output layer and the other layers are known as the hidden layers. Each layer has units known as the artificial neurons and the ReLu -Rectified linear units activation function is used to activate units. In between any two layers a parameter matrix is used which does function mapping from previous layer to next layer. Forward propagation and backward propagation are used to train the neural network.

As in the dataset, we have five classification so the output layer has only five units which gives the probability of being blind from range 0-4 which increases from 0.

In fig. 2, an example of simple neural network is shown with 3 units of input layer, 4 units of output layer and hidden layer having 5 units each.

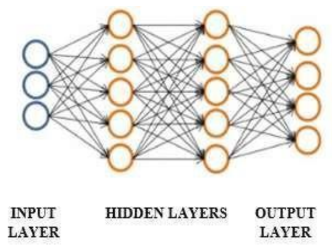

Fig 2. An example ofNeural Network

Convolution Layer

Convolution is the first layer to extract features from an input image. Convolution preserves the relationship between pixels by learning image features using small squares of input data. It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel.

An image matrix (volume) of dimension (h*w*d)

A filter (f_h * f_w * d)

Output a volume dimension

($h - f_h + 1$) * ($w - f_w + 1$) * 1

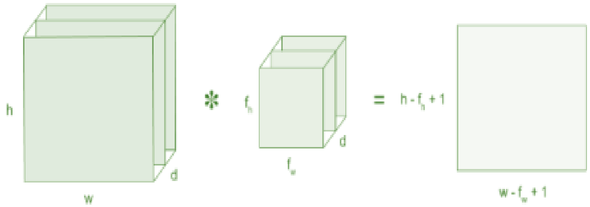

Fig. 3. Image Matrix for CNN

Strides

Stride is the number of pixels shifts over the input matrix. When the stride is 1 then we move the filters to 1 pixel at a time. When the stride is 2 then we move the filters to 2 pixels at a time and so on.

Padding

Sometimes filter does not fit perfectly fit the input image. We have two options:

1.Pad the picture with zeros (zero-padding) so that it fits

2.Drop the part of the image where the filter did not fit. This is called valid padding which keeps only valid part of the image.

Pooling Layer

Pooling layers section would reduce the number of parameters when the images are too large. Spatial pooling also called subsampling or down sampling which reduces the dimensionality of each map but retains important information.

Fully Connected Layer

The layer we call as FC layer, we flattened our matrix into vector and feed it into a fully connected layer like a neural network. The feature map matrix will be converted as vector (x1, x2, x3, …). With the fully connected layers, we combined these features together to create a model. Finally, we have an activation function such as SoftMax or sigmoid to classify the outputs.

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labelled training data (*supervised learning*), the algorithm outputs an optimal hyperplane which categorizes new examples. In two-dimensional space this hyperplane is a line dividing a plane in two parts where in each class lay in either side.

Support Vector Machines are the classification algorithms that are used to classify the examples when the number of features is very large. Sometimes, SVM gives better non-linear hypothesis than the logistic regression and the neural networks. SVMs are also referred to as large margin classifiers.

In fig. 4, graph represents large margin classification in SVM.

large margin classifiers.

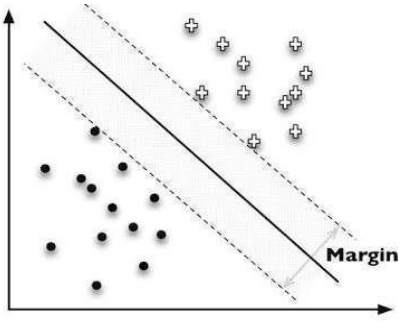

Fig. 4. An example of SVM

A supervised machine learning algorithm (as opposed to an unsupervised machine learning algorithm) is one that relies on labelled input data to learn a function that produces an appropriate output when given new unlabelled data.

The KNN algorithm assumes that similar things exist in close proximity. In other words, similar things are near to each other.

KNN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification.

Both for classification and regression, a useful technique can be to assign weights to the contributions of the neighbours, so that the nearer neighbours contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbour a weight of 1/d, where d is the distance to the neighbour.

The neighbours are taken from a set of objects for which the class (for k-NN classification) or the object property value (for k-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required.

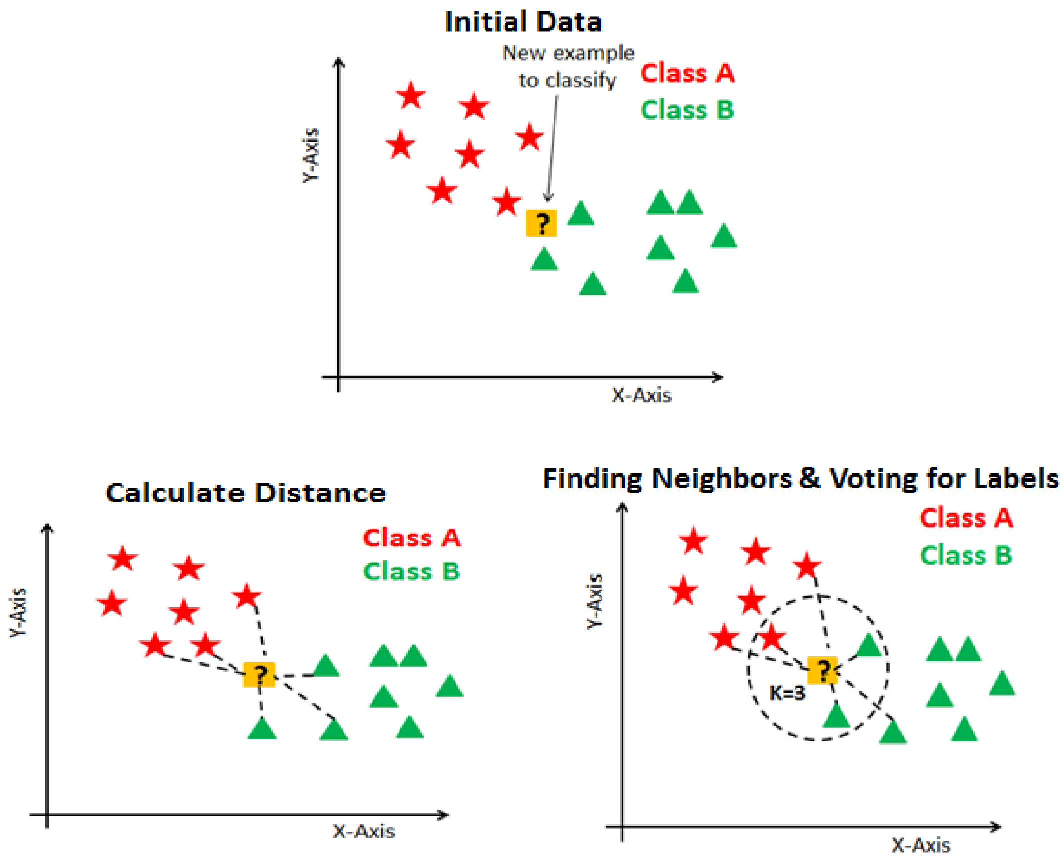

Fig.5.Steps of KNN (a).Initial Data (b).Calculation (c). Final Voting

1.Load the data
2.Initialize K to your chosen number of neighbors
3. For each example in the data
3.1 Calculate the distance between the query example and the current example from the data.
3.2 Add the distance and the index of the example to an ordered collection.
4. Sort the ordered collection of distances and indices from smallest to largest (in ascendingorder) by the distances
5. Pick the first K entries from the sorted collection
6. Get the labels of the selected K entries
7. If regression, return the mean of the K labels
8. If classification, return the mode of the K labels

III. CONCLUSION

Different types of classifier and its performance are analysed for the automated diagnosis of diabetic retinopathy from the features extracted. Performance analysis of various classifiers is done in terms of sensitivity, specificity analysis. There are several detection algorithms that have already been developed and proposed which perform satisfactorily. This survey paper can act as a resource for the future researchers interested in automated detection of abnormal signs of diabetic retinopathy and help them to get an overview of this field in order to develop more efficient algorithms.

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