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Early Detection of Diabetic Retinopathy using Fundus Images

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Abstract: ***Diabetic Retinopathy is a complication of diabetes that affects the eyes. This occurs when high blood sugar levels cause damage to the retina. The blood vessels may swell and leak or sometimes new vessels tend to grow on the retina. All these could steal the person's vision. The early stage of this disease is known as Non-Proliferative Diabetic Retinopathy characterized by macular edema and macular ischemia causing the formation of Exudates. It results in blurry vision. The advanced stage of this disease is Proliferative Retinopathy. It is characterized by neovascularization and detached retina. This type is very serious that it could steal both the central and peripheral vision. Vision loss due to Diabetic Retinopathy is sometimes irreversible.*** *However, early detection and treatment can reduce the risk of blindness by 95%*. ***Regular eye screening is the best way to detect diabetic retinopathy before you notice any changes in your sight. The proposed method increases the existing accuracy of detecting the disease using fundus images.***

Key words: Diabetic Retinopathy, micro aneurysms, haemorrhages, exudates, Support Vector Machine (SVM)

I. INTRODUCTION

Diabetic retinopathy, also known as diabetic eye disease, is a medical condition in which damage occurs to the retina due to diabetes mellitus and is a leading cause of blindness. It affects up to 80 percent of people who have had diabetes for 20 years or more. At least 90% of new cases could be reduced if there were proper treatment and monitoring of the eyes. The longer a person has diabetes, the higher his or her chances of developing diabetic retinopathy.[1] Fundus photography involves capturing a photograph of the back of the eye i.e. fundus. Specialized fundus cameras that consist of an intricate microscope attached to a flash enabled camera are used in fundus photography. The main structures that can be visualized on a fundus photo are the central and peripheral retina, optic disc and macula. Fundus photography can be performed with colored filters, or with specialized dyes including fluorescein and indocyanine green. The obtained fundus images are preprocessed using several pre processing techniques. Some of them are resizing, cropping, contrast enhancement, equalization, filtering, etc. The preprocessed images are then used to extract the features of the retina. The retinal lesions are classified as microaneurysms, haemorrhages and exudates. Once the features are extracted the SVM classifier is used to classify the severity of the disease based on the predefined classifying features. This method provides robust results and also with high accuracy.[3]

Fig. 1: Fundus image of Retina

Fig. 2: Fundus Camera

Digital Retina Cameras or Digital Fundus Cameras are used to capture images of the interior surface of the eye. Many of these Digital Retina Cameras boast features like angle variations, color, red-free and angiography imaging, high grade LCD monitors with easy to use features as well as DICOM compatibility and EMR interfacing. These images of the retina, optic disc, macula and posterior pole are digital, which enables quick transfer and detailed image study as well as side-by-side image comparison and longitudinal tracking over time. These images are key in the identification and care of various eye diseases.[4] Among most of the classification algorithm, SVM – a binary classifier is used. The main aim of SVM is to separate two classes with decision surface that has maximum margin.[5] SVM is a classifier algorithm used in medical diagnosis for the detection and classification of microaneurysms, haemorrhages and exudates in the fundus images. SVM has been applied to many problems including classification of diseases, stage detection, bioinformatics and medical diagnosis particularly for microaneurysms, haemorrhages and exudates detection in fundus images.[6]

II. RELATED WORK

Diabetic retinopathy remains a leading cause of blindness. Most cases can be prevented by timely laser photocoagulation and this requires early detection of asymptomatic retinopathy.[7] Most of systems for early DR detection that are being introduced in the literature have been proposed from fundus images. Fundus photography uses the same concept of the indirect ophthalmoscope for a wide view of the retina. One of the reasons fundus pictures are more common is that it can give a good presentation of systemic diseases.[8] L1KSFCM and L2KSFCM algorithm extracted fine details of exudates from the DR fund scope images and achieved good sensitivity and specificity. The simulation is carried out using PC and Raspberry pi 3 Model B. Further the merging features of this method can be improved with implementation of adaptive weighted membership function.[9] In the case of adaptive median thresholding approach, exudate detection accuracy is high and required less computational time but suffers from noise effects. Similarly clustering based approaches have benefits of highly elimination of noise contents but may be low accuracy in finding exudates.[10] ARIAs have reached the level of maturity to safely partake in DR screening. Future years will show if they can advance to cover a bigger part of the screening process, but for now they will be able to provide the much needed relief in the preliminary screening worldwide.[11]

III. METHODS

A. Input Image

Fundus photography documents the retina, the neurosensory tissue in our eyes which translates the optical images we see into the electrical impulses our brain understands. The retina can be photographed directly as the pupil is used as both an entrance and exit for the fundus camera's illuminating and imaging light rays. The patient sits at the fundus camera with their chin in a chin rest and their forehead against the bar. An ophthalmic photographer focuses and aligns the fundus camera. A flash fires as the photographer presses the shutter release, creating a fundus photograph of the retina. The collected images are then transferred to the computer for diagnosis, review and display.[12] From the collected images, a single static image is used to detect the disease in the Retina. The image is then processed, segmented, extracted and then classified.

B. Image Pre-processing

The real time biomedical images contain very large amount of noise as well as it is not clear to recognize accurate structure of components. The input image obtained is preprocessed to enhance image feature by removing noise and to increase brightness, etc. Some image features are very important for further processing. Image pre-processing is done to increase the reliability, to suppress

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the noise present in the image and to enhance the image. Contrast enhancement, Pixel adjustment, Cropping, Resizing followed by Filtering are done in image processing.

1) Contrast Enhancement: Contrast Enhancement is done in image processing in order to increase the quality of the images which is necessary for human interpretation. Contrast enhancement improves the visibility of an object by enhancing the brightness in the objects and in their backgrounds. The contrast can be altered by mapping the gray level values to new values in an image through a gray-level transform.

2) Resizing and cropping: Image can be resized using image scaling. This scaling will stretch an image without changing the actual pixels. Resizing actually changes the PPI (Pixel per inch) number of the image without changing the appearance of image. With bitmap graphics, the size of an image can be reduced or enlarged. Cropping is done to remove the unwanted portions in an image. Cropping removes the areas of a picture by reducing horizontal or vertical edges. Depending on application, cropping is performed on digital images using software, photograph etc. Cropping allows pictures to be viewed clearly for further processing.

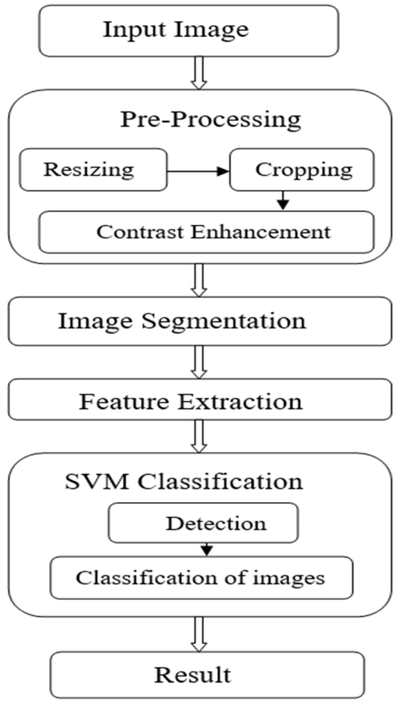

Fig. 3: Block diagram

3) Filtering: In image processing, Filters are mainly used to suppress the lower frequencies or higher frequencies in an image and to suppress the noise. Adaptive mean Filter is used to give better output image. The filtering performs processing to determine the pixel that has been affected by noise. The noise in the pixel can be found by comparing each pixel in an image with the nearest neighbourhood pixels. The noise pixels are replaced by median pixel value of pixels in the neighbourhood.

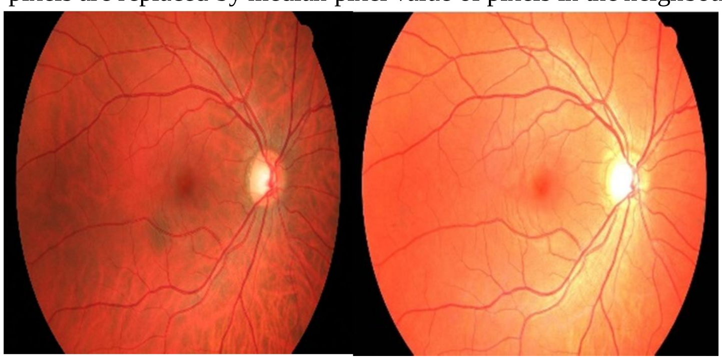

Fig. 4(a): Fig. 4(b):

Fig.4(a) and fig.4(b) shows the original and preprocessed image of the fundus image.

C. Image Segmentation:

Image segmentation is the method of dividing image into numerous segments, this represented as pixel or sub-pixels. Main aim of segmentation is to determine the boundary of interested region. In other words Image segmentation is the process of dividing an image into multiple segments (sets of pixels, also known as super pixels). The main motive of image segmentation is to modify the representation of an image that is easy to analyze. In this paper, segmentation is done with K-means clustering. The K-means algorithm is an iterative technique that is used to partition an image into K clusters. In K-means clustering the number of clusters to be partitioned must be specified and allow clusters data by iteratively computing a mean intensity for each class and segmentation of image is done by classifying each pixel with closest mean. The steps in K-means algorithm is, 1) Select K initial clusters Z1 (I), Z2 (I)… Zk(I). 2)At the Kth iterative step, distribute the samples x among the K clusters. 3)To compute the new cluster centers Zj(K+1),j=1,2,…,k, such that sum of the square distance from all points in Cj(K) to the new cluster is reduced. 4) If Zj (K+1), j=1,2…K the procedure is terminated.

D. Feature Extraction

To identify abnormalities or to classify pictures into totally different grades of diseases, feature extraction plays an important role. Feature extraction techniques are applied to get features that will be useful in recognition and classification of images. Feature extraction techniques are helpful in various image processing applications. Generally features describe the behaviour of an image they show its place in terms of storage taken, efficiency in classification and in time consumption also.

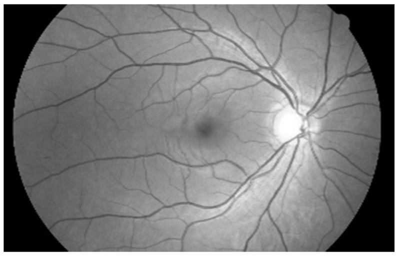

Fig. 5(a): shows the original image.

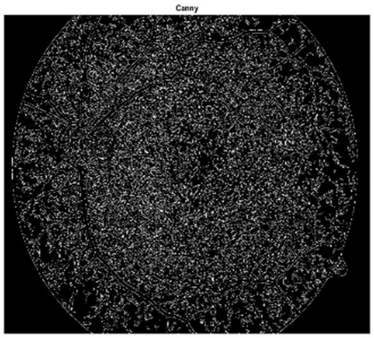

Fig.5(b) shows the segmented images.

E. Classification

It is very important and final stage of every project. Main aim of this classifier is to classify the images according to some parameters which help to identify the disease. According to survey, different classification techniques were used such as SVM (support vector machine), neural network, fuzzy classification and decision tree. In this paper SVM algorithm is used for classification of intestinal diseases.

IV. SVM CLASSIFIER

SVM is a very popular supervised learning technique among machine learning algorithms. It is used in both classification and regression problems and it has a wide range of applications. SVM algorithms have gained importance over the years due to its robustness, high accuracy and e□ectiveness . Compared to other competing classification methods, they often perform better in terms of generalization performance.

A. *The Statistical Learning Theory*

SVM formulation is based on the Statistical Learning Theory, which aims to deal with the problem of gaining knowledge from an available set of data. It provides a framework to study how to make inferences, predictions and decisions, and how to construct models from the data. Let X and Y are the input and the output spaces. In the following discussion, we will consider binary classification and use labels Y = {−1, +1} for the two classes, with −1 being a negative example and +1 a positive example. Let (x, y) ∈ (X, Y) be a training set of dimension l that is sampled according to some unknown distribution P(x, y). The main goal of a classifier is to find a mapping f: X → Y, while minimizing the expectation of the test error, also called the expected risk or just risk, which is given by,

$$R(f) = w\ c(f(x), y)dP(x,y) \qquad (1)$$

In this expression, c(f(x),y) is called the loss function and is a measure of the test error, that relates the predicted value of x with its actual value y. A common loss function used in classification problems is,

$$c(f(x),y) = 1\ 2|y-f(x)| \qquad (2)$$

This function return 0 if x is correctly classified and 1 otherwise. Since P(x,y) is an unknown distribution, usually it is not possible to minimize the expected risk. One way of getting over this is to use the Empirical Risk Minimization induction principle, which replaces the expected risk by the empirical risk. The empirical risk is defined as the mean error rate on the training set and is given by,

$$Remp(f) = \sum i=1 c(f(x),y) \qquad (3)$$

B. *Linear SVM*

Let's assume that there is a hyperplane which separates positive points, x ∈ {+1}, from negative points, x∈{−1}. The points lying in this hyperplane satisfy,

$$wTx + b = 0 \qquad (4)$$

where x is a vector point and w is the weight vector, which is perpendicular to the hyperplane and has norm ||w||. The perpendicular distance from origin to hyperplane is represented as |b| ||w||. The separating hyperplane divides the data space into two distinct regions, each one corresponding to one of the classes. In each region the data points which are nearest to the hyperplane are referred as support vectors. Support vectors are considered to be the most important data from the training set, since they are the only data points used to determine the equation of the separating hyperplane. Let d+ and d− be, respectively, the perpendicular distances from the separating hyper- plane to the closest positive and negative support vectors. H+ and H− are the hyperplanes which are parallel to the separating hyperplane and contain the support vectors. These hyperplanes are defined by,

$$H+: wTx + b = +1 \qquad (5)$$

$$H-: wTx + b = -1 \qquad (6)$$

Note that any point from the training set falls between these two hyperplanes. Thus, every training data satisfy,

$$wTxi + b \geq +1,\ yi = +1 \qquad (7)$$

$$wTxi + b \leq -1,\ yi = -1 \qquad (8)$$

Combining these two inequations yields,

$$yi(wTxi + b) \geq 1,\ \forall i \qquad (9)$$

The distances from H+ and H− to the origin are, respectively, b+1 ||w|| and b−1 ||w|| . The margin M is defined as the distance between H+ and H−, that is,

$$M = b + 1\ ||w|| b-1 ||w|| = 2\ ||w|| \qquad (10)$$

The optimal hyperplane allows separating data with the maximum margin possible and is determined by minimizing ||w||2, subject to constraints. This leads to a quadratic optimization problem.

C. *Rigid-Margin SVM*

Rigid Margin SVM defines a rigid decision boundary and does not allow any data point to lie inside the margin. The optimization problem becomes,

Minimize,

$$2||w||2 \qquad (11)$$

Subject to,

$$yi(wTxi + b) \geq 1,\ \forall i\ . \qquad (12)$$

This quadratic optimization problem is solved by switching to an unconstrained Lagrangian formulation [10, 11]. The introduction of positive Lagrangian multipliers αi, i = 1,...,l yields,

$$LP = \frac{1}{2}\|w\|^2 - \sum_i \alpha_i[y_i(w^Tx_i + b) - 1] \quad (13)$$

LP must be minimized with respect to w,b and maximized with respect to α_i. The solution is given by the saddle point. This is a convex quadratic optimization problem, since the objective function is itself convex and the points satisfying the constraints also form a convex set. For this reason, it is possible to make use of the Karush-Kuhn- Tucker (KKT) conditions to solve the problem and, therefore, the gradient of LP should vanish,

$$\frac{\partial LP}{\partial w} = 0 \Rightarrow w = \sum_i \alpha_i y_i x_i \quad (14) \qquad \frac{\partial LP}{\partial b} = 0 \Rightarrow \sum_i \alpha_i y_i = 0 \quad (15)$$

Replacing these results in equation 2.13 gives:

Maximize,

$$LD = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j x_i x_j \quad (16)$$

Subject to,

$$\sum_i \alpha_i y_i = 0 \quad (17)$$

$$\alpha_i \geq 1, \forall i \quad (18)$$

This formulation is called the dual problem, while 13 represents the primal formulation. The most important reason for using the dual formulation is that the data appear as dot products between vectors. This property becomes extremely important as it will allow generalizing the problem to deal with non-linearly separable data. Once the optimization problem is solved for α_i, w may be determined from 14. The parameter b is then found from the KKT condition [11],

$$\alpha_i(y_i(w^Tx_i + b) - 1) = 0, \forall i \quad (19)$$

D. The Non-Linearly Separable Case

In many real problems, it is not possible to find a decision boundary that exactly separates the data into two classes. This may happen due to the presence of noise or outliers or even because of the non-linear nature of the problem. SoftMargin SVM One possible approach to deal with nonlinearly separable data is to smooth the classifier boundaries, allowing some of the data to lie inside the margin. The hyperplane constraints are relaxed by introducing positive slack variables $\xi_i, i = 1,...,l$. Thus,

$$y_i(w^Tx_i + b) \geq 1 - \xi_i, \ \xi_i \geq 0, \forall i \quad (20)$$

If $0 < \xi_i < 1$, then x_i is well classified, although it is inside the margin. However, if $\xi_i \geq 1$, x_i is classified. The upper limit of the number of training errors is $\sum_i \xi_i$. Add this $\sum_i \xi_i$ to the function yields,

$$\frac{1}{2}\|w\|^2 + C\sum_i \xi_i \quad (21)$$

In this expression, C is called the regularization parameter and represents a penalty factor to the training errors. The optimization problem is, Minimize,

$$\frac{1}{2}\|w\|^2 + C\sum_i \xi_i \quad (22)$$

Subject to,

$$y_i(w^Tx_i + b) \geq 1 - \xi_i, \ \xi_i \geq 0, \forall i . \quad (23)$$

Just like in Rigid Margin SVM, the problem is solved by switching to the Lagragian formulation,

$$LP = \frac{1}{2}\|w\|^2 + C\sum_i \xi_i - \sum_i \alpha_i[y_i(w^Tx_i + b) - 1 + i] - \sum_i \mu_i \xi_i \quad (24)$$

Again, according to the KKT condition, the derivatives of LP are set to zero,

$$\frac{\partial LP}{\partial w} = 0 \Rightarrow w = \sum_i \alpha_i y_i x_i \quad (25)$$

$$\frac{\partial LP}{\partial b} = 0 \Rightarrow \sum_i \alpha_i y_i = 0 \quad (26)$$

$$\frac{\partial LP}{\partial \xi_i} = 0 \Rightarrow C - \alpha_i - \mu_i = 0 \quad (27)$$

Replacing these results in 2.24 leads to the dual formulation of the problem,

Minimize,

$$LD = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j x_i x_j \quad (28)$$

Subject to,

$$\sum_i \alpha_i y_i = 0 \quad (29)$$

$$0 \leq \alpha_i \leq C, \forall i \quad (30)$$

As before, once α_i is determined, w and b are found, Respectively, from 25 and from the KKT condition

$$\alpha_i(y_i(w^Tx_i + b) - 1 + \xi_i) = 0, \forall i \quad (31)$$

E. Non-Linear SVM

In Soft-Margin SVM, the decision boundary is a linear function of the data. Non- Linear SVM deals in the feature space corresponds to a non-linear model in the input space. This procedure is known as the Kernel Trick. The reason for doing this is based on Cover's Theorem. According to this theorem, an input space with non-linearly separable data can be mapped into a higher dimensional space (possibly infinite dimensional), in which data has high probability of being linearly separable. This will be true as long as the mapping transformation is non-linear and the dimension of the feature space is high enough.

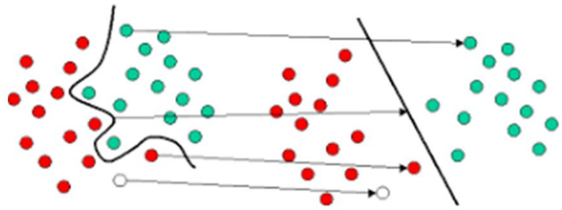

Fig. 6: The kernel trick: mapping the input space into the feature space.

Let Φ be the function which maps the input space T (low dimensional) into the feature space H (high dimensional). Thus,

$$\Phi: T \rightarrow H \qquad (32)$$

It is not hard to understand that, if the dimension of the feature space is too high, the computation of the mapping function may become too complex to be done in practice. Thus, in these cases, it is not viable to work with Φ explicitly. However, it is not really necessary to know Φ explicitly, since the only information that is required in the feature space is the dot product between the data. Given this, we use a kernel function K, which receives two data points in the input space and returns their dot product in the feature space,

$$K(xi,xj) = \Phi(xi).\Phi(xj) \qquad (33)$$

Since the kernel function uses an implicit mapping, we can directly apply it in the input space instead of calculating Φ(xi) and Φ(xj) and then taking the dot product. This makes the procedure much simpler. The most used kernels are the following, Polynomial of degree q,

$$(xixj + 1)q \qquad (34)$$

Radial Basis Function (RFB),

$$\exp(-||xi - xj||2\ 2\sigma\ ) \qquad (35)$$

Sigmoid function,

$$\tanh(\kappa xixj - \delta) \qquad (36)$$

The choice of the kernel strongly a□ects the success of an SVM classifier. Although there aren't clear rules for selecting the most e□ective kernel for a particular classification task, the RBF function usually o□ers good performance and it is definitely the most popular kernel choice.

V. CONCLUSION

The work in this paper discusses the detection of Diabetic Retinopathy by using SVM classifier algorithm. In this paper, the images are captured by Fundus Camera which provides visualization of the retina. From the collected images, a single static image is used to detect the disease. In pre-processing resizing of images is done to reduce or enlarge the size of the image, cropping is done to improve framing or aspect ratio and Adaptive mean filter is used to remove noise in the image. Pre-processed image is segmented to detect the accurate portion of the disease in intestine. The advantages of Proposed Methods are: Time consumption is low, able to get the accurate result, Low complexity and easy to detect the stages of the disease. For classification of diseases, Support Vector Machine (SVM) algorithm is employed. The future work is about finding the stages of the diseases by using the fundus images obtained from a smartphone and 3-D representation of images helps to diagnose the disease better.

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