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Diabetes Mellitus Detection using Gabor Filter

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Abstract:- Millions of people die from Diabetes Mellitus every year. Recently, researchers have discovered that Diabetes Mellitus can be detected in a non-invasive manner through the analysis of human facial blocks. Although algorithms have been developed to detect Diabetes Mellitus using facial block colour features, use of its texture features to detect this disease has not been fully investigated. In this paper, we propose a novel method to detect Diabetes Mellitus based on facial block texture features using the Gabor filter. For Diabetes Mellitus detection we first select four blocks to represent a facial image. Next, we extract texture features using the Gabor filter from each facial block to represent the samples, where each facial block is defined by a single texture value. Afterwards, k-Nearest Neighbours and Support Vector Machine are applied for classification. Experimental results on a dataset show that the proposed method can distinguish Diabetes Mellitus and Healthy samples with an accuracy of 99.82%, a sensitivity of 99.64%, and a specificity of 100%, using a combination of facial blocks.

Key Words :- *Diabetes Mellitus (DM), texture feature, color feature, Neighbourhood based Modified Back propagation using Adaptive Learning Parameters (ANMBP), Sparse Representation Classifier(SRC)K- Nearest Neighbour (KNN), Support Vector Machine(SVM), facial block, computerized iris diagnosis, simplified patch ordering and improved patch ordering.*

I. INTRODUCTION

Diabetes is a complex group of diseases with a variety of causes. People with diabetes have high blood glucose, also called high blood sugar or hyperglycemia. Diabetes is a disease in which the body is unable to properly use and store glucose. Now a days, Diabetes Mellitus can be detected in a non-invasive manner through the analysis of human facial blocks, by extracting color feature of that blocks. Non-invasive means the body is not invaded or cut open as during surgical investigations or therapeutic surgery. Until the last several decades, exploratory surgery was routinely performed when a patient was critically ill and the source of illness was not known. In dire cases, the patient's thorax, for instance, was surgically opened and examined to try to determine the source of illness. Diagnostic imaging was first performed in 1895 with the discovery of the x-ray. For the first time, physicians could see inside the body without having to perform exploratory surgery. Thus diagnostic imaging is a "non-invasive" way to look at internal organs and structures.
Here we distinguish DM samples vs. Healthy samples based on facial block texture features using the Gabor filter. We use the facial images dataset, where four blocks represent one sample with each block having one texture feature value. As the Gabor filter is similar to the human visual system, it is effective in feature extraction.

First, we generate a custom-sized 2-D Gabor filter bank. Then by using this filter bank the texture features of a facial image are calculated, where the result is a column vector. Finally, we is computed mean of the vector and assigned the texture value of the facial block. We extract texture features using the Gabor filter from each facial block to represent the samples, where each facial block is defined by a single texture value. Afterwards, *k*-Nearest Neighbors and Support Vector Machine are applied for classification.

A. Flow Chart

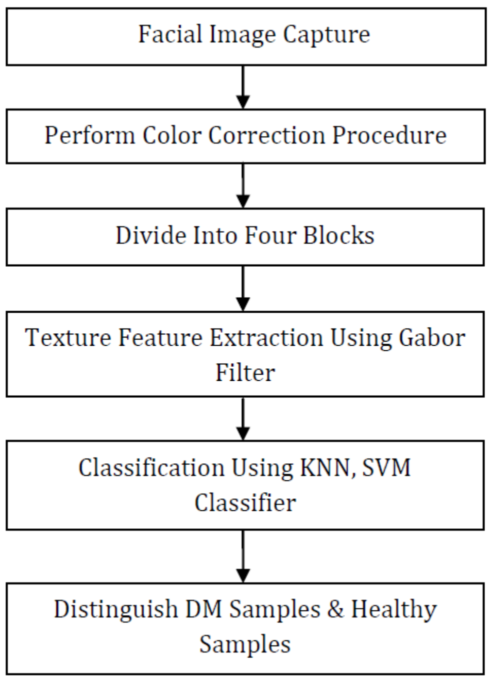

Fig.1 Flow-chart for DM detection using Gabor Filter

II. MODULE

1] We use facial block color features with the Sparse Representation Classifier(SRC) to detect DM. They classified DM vs. Healthy based on a combination of four facial blocks with the SRC. The four facial blocks were located on the forehead, the nose, and below the right and left eyes, with each block represented by 6 colours.

2] We use four blocks (A, B, C, and D) of size 64 × 64 extracted to characterize a facial image. Fig.1 shows an example of a captured facial image with the marked four blocks. Block A is taken from the forehead. Blocks B and D are symmetrical and located below the right and left eyes respectively. Block C is found on the nose, B and D's midpoint. As Blocks B and D are similar, we do not use Block D in practice. we generate a custom-sized 2-D Gabor filter bank: It is straightforward to generalize the filter in (10) to two dimensions where the time variable t is replaced by the spatial coordinates (x, y) and the frequency variable u by the frequency variable pair (u, v) and this was presented in the late 70's. If similar studies in optics are not considered, the major effort to the development and use of 2- D Gabor filters has been made in image processing and especially in feature extraction.

3] By using this filter bank the texture features of a facial image are calculated, where the result is a column vector (one texture value for each filter). Fig. 2 displays the Gabor filter bank where each row represents one σ (5 in total) and each column is an orientation (8 in total).

4] Then we compute the mean of the vector and assigned the texture value of the facial block. After extracting the facial block texture features, *k*-NN and SVM are used to classify DM samples vs. Healthy samples.

III. ALGORITHM

A. Gabor filter

A Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination.

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Facial block texture feature extraction is presented in this subsection. In order to compute the texture value of each block a 2-D Gabor filter is applied and defined as:

$$G(x,y) = \exp\frac{(x'^2 + y^2 . y'^2)}{-2\sigma^2} \cos(2\pi \frac{x'}{y})$$

where x'=x cosΘ+y sinΘ, y' = - x.sinΘ +y cosΘ

σ is the variance
λ is the wavelength
γ is the aspect ratio of the sinusoidal function
θ is the orientation.

A total of five σ (1, 2, 3, 4, and 5) and eight θ (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°) values were tested to achieve the best result. This gives us 5 × 8 = 40 2-D Gabor filters in our Gabor filter bank, and the size of each filter was set to 39 × 39. Each filter in the bank with the same σ is convolved with a facial block to produce a response

$$R_x(x,y):$$
$$R_x(x,y) = G_y(x,y) * im(x,y)$$

Where,
im(x,y) = facial block, * represents 2-D convolution and k=1,2,…….40.

The texture value of each response is the mean of all its pixels. By taking the mean of all forty texture values, the final texture value 1 of a facial block can be calculated.

Support vector machine is a machine learning method that is widely used for data analyzing and pattern recognizing. A support vector machine constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

Whereas the original problem may be stated in a finite dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. To keep the computational load reasonable, the mappings used by SVM schemes are designed to ensure that dot products may be computed easily in terms of the variables in the original space, by defining them in terms of a kernel function k(x,y) selected to suit the problem.[2] The hyperplanes in the higher-dimensional space are defined as the set of points whose dot product with a vector in that space is constant. The vectors defining the hyperplanes can be chosen to be linear combinations with parameters α_i of images of feature vectors x_i that occur in the data base. With this choice of a hyperplane, the points x in the feature space that are mapped into the hyperplane are defined by the relation: $\Sigma_i a_i k(x_i,x)$ = Constant. Note that if k(x,y) becomes small as y grows further away from x, each term in the sum measures the degree of closeness of the test point x to the corresponding data base point x_i. In this way, the sum of kernels above can be used to measure the relative nearness of each test point to the data points originating in one or the other of the sets to be discriminated. Note the fact that the set of points x mapped into any hyperplane can be quite convoluted as a result, allowing much more complex discrimination between sets which are not convex at all in the original space.

Concept: Classifying data has been one of the major parts in machine learning. The idea of support vector machine is to create a hyper plane in between data sets to indicate which class it belongs to. The challenge is to train the machine to understand structure from data and mapping with the right class label, for the best result, the hyper plane has the largest distance to the nearest training data points of any class.

IV. CONCLUSION

Mellitus Detection. Although many papers have been published on Diabetes Mellitus Detection, but the detection of DM is still an issue. Diabetes Mellitus can be detected noninvasively using different features. Feature extraction is done using Gabor Filter and classification is done using SVM and K-NN.

he choice of Gabor filter gives highest accuracy and faster result as compare to other methods. For classification of featured image classifier is used KNN which are comparatively simple algorithm,. Hence, we used separate texture features and color features for DM Detection. The Future scope can be Combine texture features with facial block color Features.

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