International Journal of Engineering Research and General Science Volume 3, Issue 2, March-April, 2015
ISSN 2091-2730

Diabetic Retinopathy Stages Detection Using Fundus Images

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Abstract— The International Diabetes Federation **(IDF)**'s Diabetes Atlas reports that India has the highest number of people with diabetes in the world, and hence considered to the "Diabetes Capital of the World". Currently, 40.9 million Indians are estimated to be suffering from diabetes. By 2025, this number will rocket to 69.9 million, and potentially 85 million by 2030. It is considered that nearly 14-22% of the population across India fall in the pre-diabetic condition. These people could get diabetes within a decade. Diabetes affects the eye in various ways and one of the ways is Diabetic Retinopathy. Diabetic retinopathy (DR) refers to damage to the retina caused by abnormal blood flow related to diabetes mellitus, which can potentially lead to severe loss of vision. Annual retinal examination and early detection of DR can considerably reduce the risk of visual loss in diabetic individuals. The analysis therefore indicates the need of detecting Diabetic Retinopathy at its early stage and preventing the loss of vision in diabetic patients. In this paper, one of the automatic methods of detection of DR levels in humans is adopted and implemented using MATLAB. The method involves the processing of fundus images in MATLAB and detecting the level of Diabetic Retinopathy in patients.

Keywords - Diabetic Retinopathy, SVM classifier, Feature Extraction, Hemorrhages, Macula Edema, Exudates, Neural Network.

INTRODUCTION

The Diabetic Retinopathy is a disease affecting the human eye. The humans suffering from diabetes have high level of glucose in the blood[22] Due to this, the blood vessels of retina may get damaged, thus affecting the vision. The retina is the light-sensitive tissue at the back of the eye. A healthy retina is necessary for good vision.

The method implemented in this paper involves automatic detection of DR levels by processing the fundus images taken from a fundus camera.

Figure.1: Fundus image

The Diabetic Retinopathy is divided into three levels depending upon the features present in the DR affected fundus images. [20][1]. The fundus images are pre-processed involving Grey Scale Conversion of RBG fundus images followed by removing of noise using Median Filtering Technique and finally improving the contrast of images using Histogram Equalization technique. The pre-processed fundus images are then fed for Segmentation using Histogram Segmentation Technique. The segmented output is further fed to

feature extraction level wherein various feature of segmented output is calculated. The feature vector is then designed based on the features extracted which are then fed to an SVM classifier. The SVM classifier is designed in such a way that it measures the level of DR in patients based on the type (Haemorrhages, Macula Edema and Exudates) of structures present in the fundus image[9].

Haemorrhages result due to leakage of retinal blood vessels. They have a similar red colour to the vessels.It indicates Mild Diabetic Retinopathy. Macula Edema is retinal thickening within 2 disc diameters of the centre of the macula, results from retinal microvascular changes that compromise the blood-retinal barrier, causing leakage of plasma constituents into the surrounding retina. It indicates Moderate Diabetic Retinopathy. Exudates are bright yellow-white deposits on the retina due to the leakage of blood from abnormal vessels. It indicates Severe Diabetic Retinopathy.

FUNDUS IMAGE PRE-PROCESSING

Pre-processing of fundus images is required in order to obtain an image which is noise free and contrast enhanced. The pre-processing of Fundus images includes the following steps:

- Conversion of RGB to grey scale image
- Noise removal using Median Filtering
- Histogram Equalization for contrast enhancement

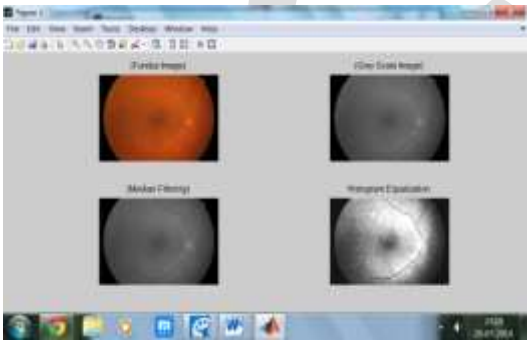

Figure 2: Output of Pre-processed Fundus images

SEGMENTATION USING HISTOGRAM THRESHOLDING

In Histogram Thresholding, based on the histogram obtained for a particular pre-processed image, a threshold point is selected. This threshold value will segment the image in order to obtain the required contour (region of interest).

Figure3a: Output of Segmentation of Fundus Images- presence of Haemorrhages

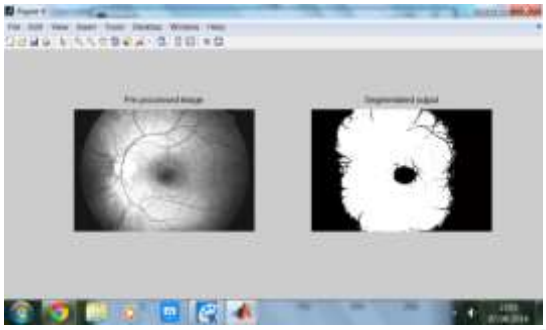

Figure3b: Output of Segmentation of Fundus Images- presence of Macula Edema

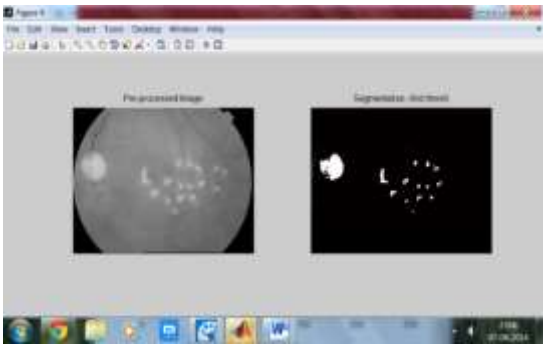

Figure3c: Output of Segmentation of Fundus Images- presence of Exudates

FEAUTRE EXTRACTION

The feature extraction includes evaluating the various features of a segmented image in order to form a feature vector required to input the SVM classifier. The feature extraction is a process wherein various features of the segmented image are extracted. In order to capture the spatial dependence of grey-level values, a two-dimensional dependence matrix known as a grey-level co-occurrence matrix (GLCM) is extensively used. The grey-level co-occurrence matrix P [i, j] is defined by first specifying a displacement vector d = (dx, dy) and counting all pairs of pixels separated by 'd' having grey levels 'i' and 'j' [23].

The following are the features which are extracted from segmented images:

1. **ENERGY:** Energy corresponds to the mean squared value of the image typically measured with respect to the global mean value. Energy of an image returns the sum of squared elements in the GLCM.

$$Energy = \sum_{i,j} [p(i,j)]^2 \qquad (1)$$

2. **CONTRAST:** The contrast function enhances the contrast of an image. Contrast of an image returns a measure of the intensity contrast between a pixel and its neighbour over the whole image.

$$Contrast = \sum_{i,j} |i-j|^2 * p(i,j) \qquad (2)$$

3. **CORRELATION:** The operation called *correlation* is closely related to convolution. In correlation, the value of an output pixel is also computed as a weighted sum of neighbouring pixels. The difference is that the matrix of weights, in this case called the *correlation kernel*, is not rotated during the computation. The correlation operation therefore returns a measure of how correlated a pixel is to its neighbour over the whole image.

$$Correlation = \sum_{i,j} \frac{[(i-\mu i)*(j-\mu j)*p(i,j)]}{[\sigma_{i*}\sigma_j]} \qquad (3)$$

4. **HOMOGENEITY:** Homogeneity reflects the uniformity of several pixels in an image and expresses how similar all of them are. Homogeneity of image returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$Homogeneity = \sum_{i,j} \frac{[p(i,j)]}{[1+|i-j|]} \qquad (4)$$

5. **ENTROPY:** Entropy is a feature which measures the randomness of grey-level distribution.

$$Entropy = -\sum_{i,j} p(i,j) * \log 2(p(i,j)) \qquad (5)$$

The features extracted are fed to SVM classifier to classify the mages for levels of DR in patients.

CLASSIFICATION USING SVM CLASSIFIER

In machine learning, support vector machines (SVMs, also support vector networks are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification.

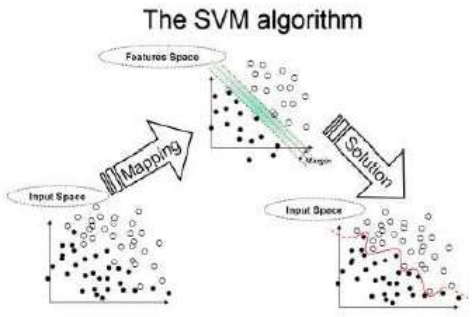

Figure 4: SVM Technique

The SVM classifier is a technique in which, the classifier undergoes two phases: Learning/Training phase and Testing Phase. The Learning Phase is wherein the classifier is made to learn the known set of images. Here the feature vector of each known image is fed to the classifier and the output is labeled accordingly. The Testing Phase is wherein the unknown images' feature vector is fed to the classifier and based on its mapping with the Learning Phase, the image is classified appropriately. The table 1.1 shows the training data images along with its features extracted in order to train SVM for detection of macula Edema. The presence of Macula Edema indicates Moderate Level of Diabetic Retinopathy. The table 1.2 shows the training data images along with its features extracted in order to train SVM for detection of Exudates. The presence of Exudates indicates Severe Level of Diabetic Retinopathy. The table 1.3 shows the training data images along with its features extracted in order to train SVM for detection of Hemorrhages. The presence of Hemorrhages indicates Mild Level of Diabetic Retinopathy.

Table1a: Training image-sets to SVM for detection of Macula Edema

	Feature Extraction				
Training data Images	Energy	Correlation	Contrast	Homogeneity	Entropy
Tr_image1	2.3437e-007	0.0224	1.4515e+006	0.0043	0.9987

Tr_image2	2.3785e-007	0.0081	1.5259e+006	0.0043	0.9995
Tr_image3	2.3437e-007	0.0224	1.4515e+006	0.0043	0.9987
Tr_image4	2.3650e-007	0.0266	1.4063e+006	0.0044	0.9992
Tr_image5	2.3353e-007	0.0099	1.4135e+006	0.0042	0.9985
Tr_image6	2.3489e-007	0.0182	1.4112e+006	0.0044	0.9988
Tr_image7	2.3785e-007	0.0081	1.5259e+006	0.0043	0.9995
Tr_image8	2.3444e-007	0.0272	1.4721e+006	0.0042	0.9987
Tr_image9	2.3890e-007	0.0107	1.6075e+006	0.0043	0.9996
Tr_image10	2.3870e-007	0.0171	1.3228e+006	0.0045	0.9996
Tr_image11	2.3599e-007	0.0178	1.3786e+006	0.0045	0.9991
Tr_image12	4.3353e-006	-0.0070	8.6766e+004	0.0152	0.9987
Tr_image13	4.4948e-006	-0.0042	7.6070e+004	0.0153	1.0000
Tr_image14	4.4581e-006	-0.0058	8.2679e+004	0.0149	0.9999
Tr_image15	4.3973e-006	-0.0042	8.2831e+004	0.0155	0.9994
Tr_image16	4.3317e-006	-0.0070	8.1668e+004	0.0152	0.9986
Tr_image17	4.3261e-006	-0.0124	9.2363e+004	0.0149	0.9985
Tr_image18	4.3803e-006	-0.0106	7.8395e+004	0.0149	0.9993
Tr_image19	4.3527e-006	-0.0053	7.6950e+004	0.0146	0.9989
Tr_image20	4.4061e-006	-0.0110	7.8107e+004	0.0148	0.9995

Table 1b: Training image-sets to SVM for detection of Exudates

	Feature Extraction				
Training data Images	Energy	Correlation	Contrast	Homogeneity	Entropy
Tr_image1	4.5775e-005	0.0581	1.1252e+006	0.0015	0.0267
Tr_image2	1.0624e-004	-0.0056	1.2374e+005	0.0217	0.1486
Tr_image3	2.4432e-004	-0.0176	9.8072e+004	0.0227	0.0758
Tr_image4	1.0036e-004	0.0900	1.0062e+005	0.0202	0.1554

Tr_image5	1.7352e-004	0.1678	8.5385e+004	0.0072	0.1003
Tr_image6	3.7736e-004	-0.0799	1.3047e+005	0.0093	0.0528
Tr_image7	4.1590e-005	0.0186	9.2517e+004	0.0166	0.3046
Tr_image8	3.7649e-005	-0.0297	8.4959e+004	0.0159	0.3276
Tr_image9	1.4096e-004	-0.0204	1.0413e+005	0.0167	0.1186
Tr_image10	1.9732e-004	0.0152	8.5114e+004	0.0073	0.0903
Tr_image11	5.1073e-004	-0.0292	1.2065e+006	0.0013	0.0032
Tr_image12	5.1073e-004	-0.0292	1.2065e+006	0.0013	0.0032
Tr_image13	0	0	0	0	0
Tr_image14	0	0	0	0	0
Tr_image15	4.3706e-004	-0.0267	1.2646e+006	0.0013	0.0037
Tr_image16	0	0	0	0	0
Tr_image17	0	0	0	0	0
Tr_image18	7.1332e-005	0.0394	2.2738e+006	0.0012	0.0182
Tr_image19	0.0051	-0.1225	2.5595e+005	0.0054	0.0016
Tr_image20	0	0	0	0	0

Table1c: Training image-sets to SVM for detection of Haemorrhages

	Feature Extraction				
Training data Images	Energy	Correlation	Contrast	Homogeneity	Entropy
Tr_image1	2.9869e-005	-0.0136	1.0753e+005	0.0122	0.3868
Tr_image2	2.8842e-005	0.0472	1.0139e+005	0.0150	0.3964
Tr_image3	2.8106e-005	0.0501	6.7139e+004	0.0144	0.4037
Tr_image4	2.9389e-005	0.0507	1.0292e+005	0.0169	0.4093
Tr_image5	7.1332e-005	0.0394	2.2738e+006	0.0012	0.0182
Tr_image6	7.1332e-005	0.0394	2.2738e+006	0.0012	0.0182
Tr_image7	0.0051	-0.1225	2.5595e+005	0.0054	0.0016
Tr_image8	4.1590e-005	0.0186	9.2517e+004	0.0166	0.3046

Tr_image9	3.7649e-005	-0.0297	8.4959e+004	0.0159	0.3276
Tr_image10	1.4096e-004	-0.0204	1.0413e+005	0.0167	0.1186
Tr_image11	1.0624e-004	-0.0056	1.2374e+005	0.0217	0.1486
Tr_image12	2.4432e-004	-0.0176	9.8072e+004	0.0227	0.0758
Tr_image13	1.0036e-004	0.0900	1.0062e+005	0.0202	0.1554
Tr_image14	2.3353e-007	0.0099	1.4135e+006	0.0042	0.9985
Tr_image15	2.3489e-007	0.0182	1.4112e+006	0.0044	0.9988
Tr_image16	2.3785e-007	0.0081	1.5259e+006	0.0043	0.9995
Tr_image17	2.3444e-007	0.0272	1.4721e+006	0.0042	0.9987
Tr_image18	4.3317e-006	-0.0070	8.1668e+004	0.0152	0.9986
Tr_image19	4.3261e-006	-0.0124	9.2363e+004	0.0149	0.9985
Tr_image20	4.3803e-006	-0.0106	7.8395e+004	0.0149	0.9993

RESULTS

The Diabetic Retinopathy (DR) level in humans can be detected by scanning the human fundus image for the presence of Macula Edema, Haemorrhages and Exudates. Macula Edema indicates Moderate level of DR, Haemorrhages indicates Mild Level of DR and Exudates indicate Severe level of DR in humans. The SVM classifier is trained with 100 fundus images which show different levels of DR. The input test image fed to the classifier appropriately classifies the level of DR based on the training of SVM Classifier.

The segmented output as shown in figure (3a) shows presence of Haemorrhages. The features are extracted of this segmented image and then the features are subjected to SVM classifier. The output of the classifier is as shown in figure (5a). The segmented output as shown in figure (3b) shows presence of Macula Edema. The features are extracted of this segmented image and then the features are subjected to SVM classifier. The output of the classifier is as shown in figure (5b). The segmented output as shown in figure (3c) shows presence of Exudates. The features are extracted of this segmented image and then the features are subjected to SVM classifier. The output of the classifier is as shown in figure (5c).

Figure 5a: SVM classifier output showing patient suffering from Mild DR

Figure 5b: SVM classifier output showing patient suffering from Moderate DR

Figure 5c: SVM classifier output showing patient suffering from Severe DR

CONCLUSION

The method adopted in this paper for early detection of DR disease in humans is reliable and shows accurate results. The method implemented can be used for screening of patients eyeballs for detecting level of DR in a cost effective manner.This technique helps in determining levels of DR in its early stage and thus preventing vision loss.

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