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DIABETIC RETINOPATHY DETECTION BY THE USE OF DEEP LEARNING APPROACH

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Abstract- Machine learning operated on images can handle smaller amount of data. Diseases are common and data set is expanding. In order to handle large set of data deep learning mechanism is required. So the proposed system uses deep learning with CNN to classify the diabetic retinopathy. The classes are multiple in nature hence multi class identification in cooperated within the proposed literature. The image enhancement is also required during the pre processing phase. This also in cooperated to handle large set of images. In other words handling large image set having more images is made feasible using this technique. The results obtained are in terms of accuracy. The obtained result is better by 5% proving woth of the study.
Keywords: Machine learning, CNN, accuracy, deep learning

1. INTRODUCTION

Diabetic retinopathy (DR) is a chronic disease related with the eye retina which presently comprises of one of the most common causes of blindness and loss of vision. The incidental statistics indicate that DR is the primary cause of blindness in people of working age of the present era. DR is an outcome of diabetes-mellitus, illness which elevates the concentration of glucose in blood. This unusually high glucose levels damage the eye vessel endothelium infuriating set of damages related to the illness. Although having diabetes does not necessarily entail vision mutilation, about 2% of the patients affected by this disease are blind and 10% undergo vision deprivation after 15 years of diabetes as a result of DR complications. Vision-threatening retinopathy is rare in type 1 diabetic patients in the first 3–5 years of diabetes or before puberty. During the next two decades, nearly all type 1 diabetic patients develop retinopathy. Up to 21% of patients with type 2 diabetes have retinopathy at the time of first diagnosis of diabetes, and most develop some degree of retinopathy over time. The estimated prevalence of diabetes for all age groups worldwide was 2.8% in 2000 and will be 4.4% in 2030.

Despite DR being an incurable disease, if the illness is detected and treated in its early stages visual impairment can be avoided in 98% of cases. In this respect, though laser photocoagulation has established to be a successful treatment for preventing major loss of vision produced by DR yet the early detection of the illness is still a difficult task since people affected by it do not recognize symptoms until visual loss develops which usually happens in the later disease stages, when treatment loses its effectiveness. This is why the prone diabetic population has to be examined periodically by public or private health systems in search of early DR signs. However, this preventive action involves a daring confrontation by the health systems due to the high number of ophthalmologists and material resources needed to attend so many patients requiring ophthalmologic revision. Hence, this paper proposes another computerized handling of retinal images with a specific end goal to help individuals recognize diabetic retinopathy in advance. The end goal of proposed literature is to achieve desired level of classification accuracy by reducing noise levels from within the 1-3 levels of non-proliferative dataset where ‘1’ indicates mild DR, ‘2’ indicates moderate DR and ‘3’ indicates severe or proliferative DR. Noise handling through Gaussian filtering is used at pre-processing stage. Gaussian filter is capable of handling noise at edges and also considered the best filters in time domain. Resizing operation is done at preprocessing stage thus, ensuring uniformity along the input layer for faster operation. MSVM gives multiclass segmentation and classification operation.

2. LITERATURE SURVEY

The existing studies and various researchers have investigated the domain of Automated diagnosis of Diabetic Retinopathy. This review, therefore, is an attempt to critically explore the literature in the area of machine learning and deep learning techniques used for DR detection culminating the process with derivation of a comparison between the two.

(Jen Hong Tan et al, 2017, Automated Segmentation of Exudates, Hemorrhages, Microaneurysms using Single Convolutional Neural Network)The paper proposes to use a 10-layer convolutional neural network to automatically concurrently segment and differentiate exudates, hemorrhages and micro-aneurysms. Input images were normalized before segmentation. (Doshi et al, 2016, Diabetic Retinopathy Detection using Deep Convolutional Neural Networks)This paper aims at automatic diagnosis of DR into different stages using deep learning. The design and implementation of GPU accelerated deep convolutional neural networks to automatically diagnose has been presented hence classifying high-

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resolution retinal images into 5 stages of the disease based on severity. (Gargeya et al, 2016, Automated Identification of Diabetic Retinopathy Using Deep Learning)This paper presents the development followed by an evaluation of a data-driven deep learning algorithm as a diagnostic tool for automated DR detection. The algorithm processed color fundus images and besides classifying them as healthy (no retinopathy) or having DR. A total of 75 137 publicly available fundus images from diabetic patients were used to train and test this model to differentiate healthy fundi from those with DR. (Grinsven, 2016, Fast convolutional neural network training using selective data sampling: Application to hemorrhage detection in color fundus images)The proposed method provides an improvement and speed-up of the CNN trained for medical image analysis tasks by dynamically selecting misclassified negative samples. Heuristic sampling of training samples is done based on classification by the current status of the CNN. Weights are then assigned to the training samples. A comparison has also been performed between the two i.e., CNN with (SeS) and without (NSeS) the selective sampling method.

3. DATSET DESCRIPTION

The image dataset used is DIARETDB0 consisting of 3 categories of 200 eye fundus images. Resizing operation manually as well as automated mechanism is posted upon to fit into the input layer of the network. The images were captured and resized to 77x100 with 3 color channels.

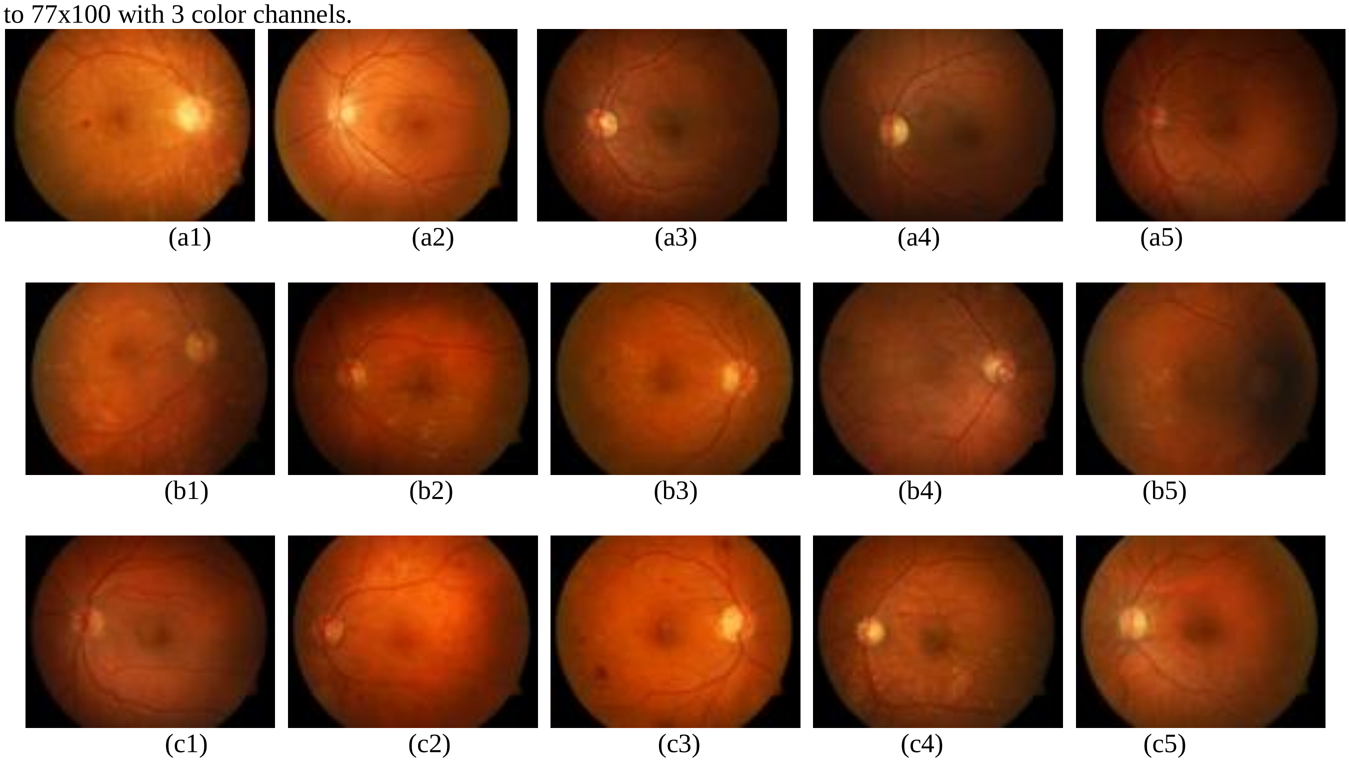


Figure 1: Fig. 1.a) mild non-retinopathy images: (b) moderate non-retinopathy images, (c) Severe non-proliferative retinopathy images.

The 200 pictures are bundled in 3 sets, one for each ophthalmologic division, utilizing the PNG format. In addition, an Excel record with therapeutic conclusions for each picture is given. In this work, we utilize the pictures of only one ophthalmologic division containing 48 pictures with mild, 48 with moderate and 48 with severe DR cases.

3. PROPOSED SYSTEM

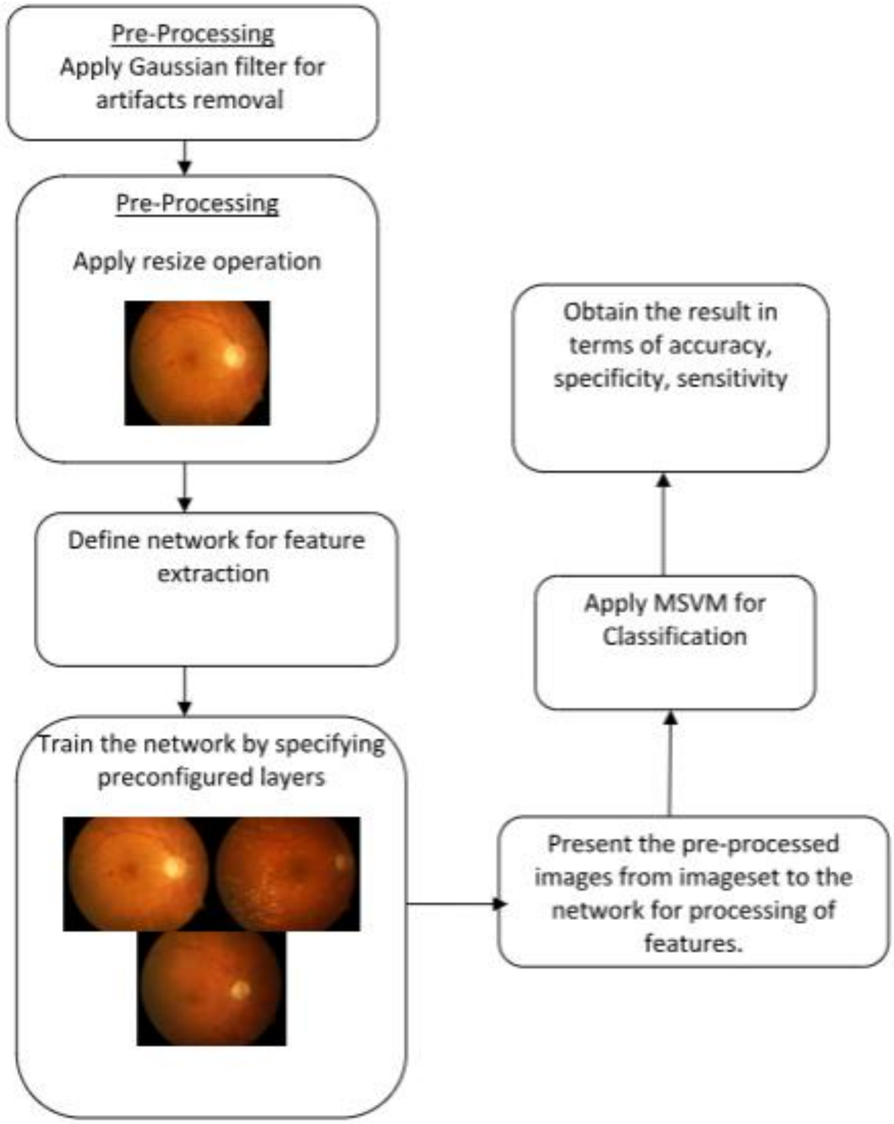


Figure 2: Flowchart showing the flow of operation

4. PERFORMANCE ANALYSIS AND RESULTS

The performance of the system is analyzed by the use of parameters such as accuracy, specificity and sensitivity.

Accuracy is obtained by subtracting the actual result from the approximate result. In terms of predictions accuracy is obtained as

$$Accuracy = \frac{Correct_{Pre}}{Total_{Pred}}$$

Equation 5: Accuracy in terms of prediction

Sensitivity is obtained by dividing number of positive predictions to the total true positive rate.

$$\text{Sensitivity=} \frac{Correct_{Positive_{pr}}}{Total_{Positi}}$$

Equation 6: Sensitivity evaluation formula

Specificity is another parameter used to evaluate correctness of the proposed system. It is given as under

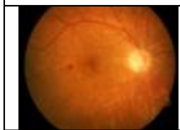
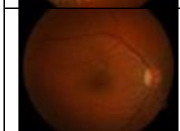
$$\text{Specificity=} \frac{True}{T_{i}}$$

Equation 7: Specificity obtaining formula

The disease detection and prediction is given though accurate classification, result in terms of plots is given as under

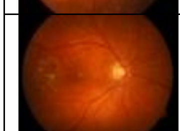
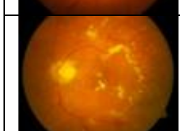
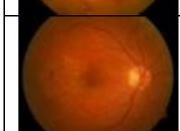
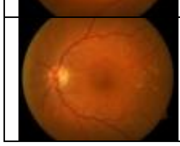
For level 1 DR image set accuracy is given as under

Table 1: Predicted accuracy corresponding to (Mild) non-proliferative retinopathy images (level 1)

Imageset	Accuracy with Deep Learning and decision tree classifiers(%)	Accuracy with MSVM(%)
	76	82
	78	85
	79	84
	78	83
	79	82

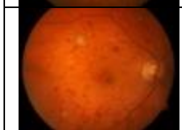
For level 2 retinopathy image set accuracy is given as under

Table 2: classification accuracy for (Moderate) non-proliferative diabetic retinopathy images

Imageset	Accuracy with Deep Learning and decision tree classifiers(%)	Accuracy with MSVM(%)
	78	82
	79	84
	78	82
	77	81
	76	82

For level 3 image set accuracy is given as under

Table 3: prediction accuracy of image set (Severe) non-proliferative diabetic retinopathy images.

Imageset	Accuracy with Deep Learning and decision tree classifiers(%)	Accuracy with MSVM(%)
	78	82
	77	81
	75	80
	76	81
	78	82

Result comparison in terms of accuracy, sensitivity and specificity are given as under

Table 4: Result comparison in terms of accuracy, sensitivity and specificity

Image set name	Parameters	Existing (%)	Proposed(%)
Level 1 DR(Mild)	Accuracy Specificity Sensitivity	75 73 78	81 80 82
Level 2 DR(Moderate)	Accuracy Specificity Sensitivity	77 79 78	82 82 84
Level 3 DR(Severe)	Accuracy Specificity Sensitivity	78 79 78	83 84 82

Classification accuracy of proposed system appears to be more as compared to existing techniques. Multiple class prediction mechanism showing higher accuracy proving the worth of study.

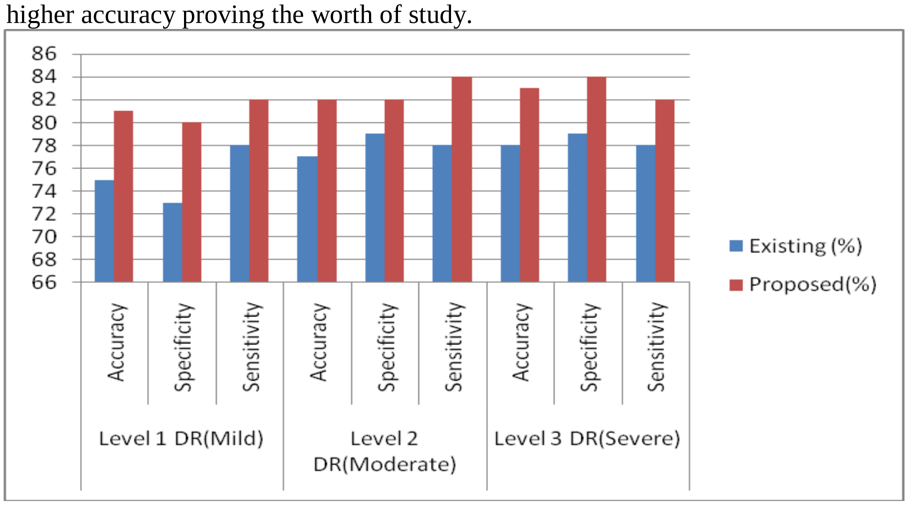


Figure 3Confusion matrix:

Results and performance analysis as indicated through the plot shows that deep learning combined with multi support vector machine yield better result.

5. CONCLUSION AND FUTURE SCOPE

Deep Learning mechanism can handle large dataset. However slight change in the present dataset could lead to drastic change in result due to ambiguity problem present within existing literature. In order to tackle the issue, stable data presentation by handling noise within the image is considered in considered approach. The decision tree classification is complex and could lead to indifferent results and to tackle the issue Support vector machine can be used since it is resilient in case noisy data is presented to the model. Overall classification accuracy could improve by the application SVM.

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