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Abstract. Microaneurysms (MAs) are the early noticeable lesions in retina, their detection plays a crucial role in the diagnosis of diabetic retinopathy. Here the discriminative features are automatically learned in an unsupervised manner. The stacked sparse auto-encoder (SSAE) is effective at learning high-level features from overlapping image patches during training. Using 10-fold cross-validation and fine-tuning yield an improved F-measure of 97.3% and an average area under the ROC curve (AUC) 96.7% obtained. Experimental validation is performed, both quantitative and qualitative, in the public datasetDIARETDB1. The result achieved a better accuracy compared to other methods.

INTRODUCTION

Many retinal diseases, including age-related macular degeneration, atherosclerosis, glaucoma, and diabetic retinopathy (DR) are analysed using digital retinal imaging [1]. One of the major causes of adult blindness worldwide is due to these disorders. Therefore, early recognition and analysis of such diseases are essential. For this, computer-aided tools can be quite beneficial [2]. For precise manual or automatic recognition and analysis, retinal images must be of the highest quality. Uneven lighting, blurring, artefacts, the spherical geometry of the eye, and operators with varied levels of competence are the main reasons to low quality in fundus imaging [3]. Some pathological features, such as haemorrhages, micro- aneurysms, and ischemic alterations, are typically only minute pixels wide and have circular forms, making them easily mistaken for noise and artefacts. Therefore, the enhancement of image quality may be crucial to improve the diagnostic potential of retinal images [4].

The pre-processing stages are used to improve retinal image quality. Blood vessel recognition and the length of discernible tiny vessels around the fovea were employed in two separate investigations to rate the image quality [1]. The histogram determination approach was used as the initial step in pre-processing for the segmentation of retinal images [7]. In addition, Contrast Limited Adaptive Histogram Equalization (CLAHE) has also been done on retinal fundus images to improve neighbourhood contrast [8-10]. An on-going report utilized CLAHE to extract the boundaries of the optic disc by modifying the non-uniform environment and adjusting contrast [12]. In another investigation, a customised quotient-based approach and non-uniform illumination model were applied to address the non-uniform brightening in fundus fluorescein angiograms [13].

Through a multi-layer neural network, deep Convolutional Neural Network (CNN) models are able to extract important characteristics from the input data [15]. It is necessary to choose the ideal network structure, loss function, and optimization technique before building a deep learning model. Deep learning models demand a lot of computer power than machine learning methods. In unsupervised learning algorithms, such as Restricted Boltzmann Machine (RBM) [16], Deep Belief Network [5], Auto-encoders [17], and Stacked Auto-encoders [6], unlabelled data are utilized to learn features while a limited quantity of labelled data is used to fine tune the parameters. The Stacked Sparse Auto encoder (SSAE) is an encoder- decoder architecture in which the 'Encoder' network models pixel intensities using low dimensional properties whereas the 'Decoder' network uses the low dimensional information to recover the original pixel intensities [14].

The suggested method offers very accurate microaneurysm detection with a short execution time. The remainder of this paper is structured as follows: Section 2, Image pre-processing is discussed. Feature extraction and classification in Section 3, Experimental findings and performance evaluation are presented in Section 4. Finally, the conclusions are stated in Section 5.

PRE-PROCESSING OF IMAGES

Acquisition of Image from dataset

The DIARETDB1 public dataset comprises of 89 colour fundus photos, 84 of which have at least mild non-proliferative evidence of diabetic retinopathy (Microaneurysms) and 5 normal images. The digital fundus camera with a 50-degree field of view was used with various image settings.

Data Pre-processing

Prior to feature extraction, data pre-processing is done on the raw fundus images. Noise typically results from using a damaged sensor to take photos or from using a noisy channel to transfer images. Based on the quantity of "noise-free pixels" in the surrounding area, an Adaptive Median Filter adapts the size of the median filter. The internal details are made visible, and here the RMSE value is low. It reduces distortions and excessive boundary thinning and thickening. During the process neighbourhood size is altered with an adaptive median filter.

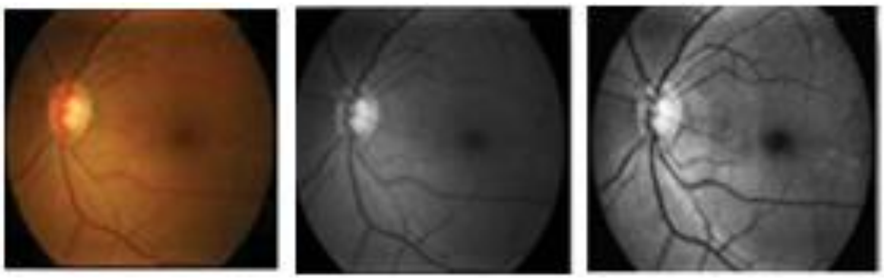

FIGURE 1. Enhancement of fundus image a) Input Image b) Green Image c) Enhance Image

Contrast-Limited Adaptive Histogram Equalization (CLAHE) operates on discrete, or tiled, portions of the image rather than the whole image. Bilinear interpolation is then used to join the neighbouring tiles, eliminating artificially induced borders. Figure 1 shows the image enhancement of the sample fundus image. CLAHE was developed for the following limits:

- To prevent the over-amplification of noise.
- To upturn contrast.
- To introduces large fluctuations in the pixel grey levels.
- To the introduction of the processing artifacts and effect of the verdict.

Patch Generation

Due to the various diameters of the microaneurysms, the data preparation is standardised. The fundus image with a patch size of 25×25 was used in the patch-based analysis into two different groups: MAs and non-MAs. All patches were collected and extracted throughout the patch generation step without any form of overlap. A total of 2182 MA image patches and by using sliding window, 6230 non-MA image patches were produced with annotations. Figure 2 demonstrates the process of MA detection.

Feature Extraction and classification

The Stacked Sparse Auto Encoder is represented in figure 3. First normalize the input patches in range [0,1]. There are 625 input units and the neurons in first hidden layer is 225 units and second hidden layer is 100 units. Here, penalise the weights in two hidden layers by introducing a regularisation function Ω, to the error function so as to achieve sparsity. The sparse autoencoder's cost functionE_{SSAE}, can be illustrated as in equation (1):

$$E_{SSAE} = E_{MSE} + \Omega \tag{1}$$

The regularisation function,Ω and the mean squared error function, E_{MSE} are both represented as in equation (2) and (3):

$$E_{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(x_i - h_i^2\right)^2 \tag{2}$$

where x_{i}input,h_i^2output of stacked sparse encoder and n, the input features.

$$\Omega = \frac{1}{n}\sum_{i=1}^{n}\left[(x_i + 10)log\frac{(x_i+10)}{(h_i^2+10)} + (10 - x_i)log\frac{(10-x_i)}{(10-h_i^2)}\right] \tag{3}$$

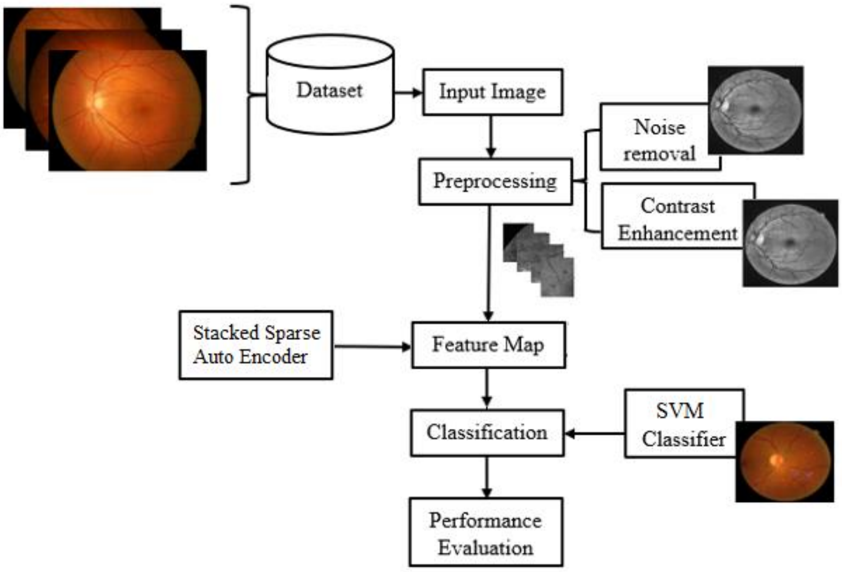

FIGURE 2. Proposed Architecture

The output layer's bias and weights are updated using stochastic gradient descent [11].As a result, one input, two hidden layers, and a final sigmoid layer were stacked to create the SSAE and interpret the results as probabilities using sigmoid function. The weights and biases of the sigmoid layer and SSAEs were jointly optimised for fine-tuning.

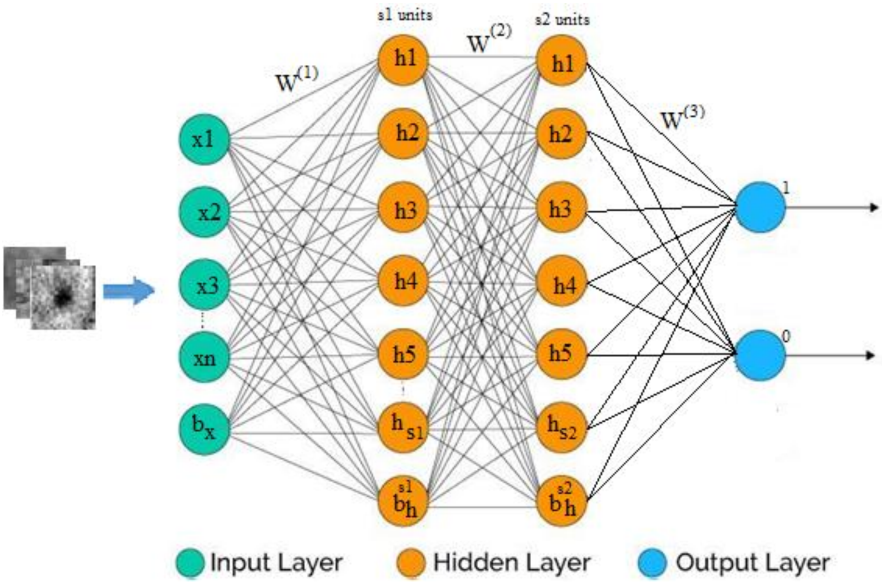

FIGURE 3: Unsupervised SSAE with sigmoid classifier

For MA detection, an SVM classifier has been employed. The image is divided into two classes, such as MA and Non-MA. The parameters were calculated using the characteristics of microaneurysms. SVM works on learning theory developed by Bladimir Vapnik. The threshold is measured by the average number of MA and its size. The parameters of the SVM have been trained using a linear kernel with fivefold validation. New testing data is fed to the SVM classifier after training, which gives better results.

RESULTS AND DISCUSSION

Accuracy, sensitivity (recall), specificity, precision, F-score and ROC curve are common measures for determining the effectiveness of classification systems is represented as in equation (4-8).

$$ACCURACY = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$PRECISION = \frac{TP}{TP + FP} \tag{5}$$

$$RECALL\ or\ SENSITIVITY = \frac{TP}{TP + FN} \tag{6}$$

$$SPECIFICITY = \frac{TN}{TN + FP} \tag{7}$$

$$F1\ SCORE = \frac{2 * TP}{2TP + FP + FN} \tag{8}$$

where TP (True positive) correctly predicts MA as MA, FP (False-positive) wrongly predicts non-MA as MA, TN (True negative) correctly predicts non-MA as non-MA, FN (False-negative) wrongly predicts MA as non-MA.

TABLE 1. Performance on DIARETB1

Algorithm	Accuracy	Precision	Recall	F1 Score
Auto-encoder	91.83	91.1	89.6	90.4
SVM	93.7	93.5	92	93
SAE+ Softmax	96	95	97	96
Proposed	98.2	97.7	96.8	97.3

The effectiveness of the suggested approach is tested against different algorithms, including Auto-encoder, Support Vector Machine (SVM) and Sparse Auto-encoder (SAE) with Softmax is shown in Table 1. The patch size has a significant impact on SSAE performance; however, fine adjustment improved the performance.

CONCLUSION

In this paper, an Unsupervised learning method such as Stacked Sparse Auto-encoder is projected to solve the difficulty that arises in the feature extraction of retinal images in the field of DR. The experiments show that the suggested method is more effective than the traditional methods and the suggested Stacked Auto-encoder with SVM model demonstrates 98.4% accuracy using the DIARETBD1 dataset. With the help of the high-level characteristics from SSAE, the SVM classifier can identify MA lesions from the fundus image with noisy background. Future studies will perform on additional performance metrics, such as computing speed, training time, classification time and other metrics, which may be helpful in evaluating the model's performance assessment.

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