Classification of Diabetic Retinopathy using Stacked Autoencoder-Based Deep Neural Network

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Abstract: Diagnosis of diabetic retinopathy (DR) via images of colour fundus requires experienced clinicians to determine the presence and importance of a large number of small characteristics. This work proposes and named Adapted Stacked AutoEncoder (ASAE-DNN) a novel deep learning framework for diabetic retinopathy (DR), three hidden layers have been used to extract features and classify them then use a Softmax classification. The models proposed are checked on Messidor's data set, including 800 training images and 150 test images. Exactness, accuracy, time, recall and calculation are assessed for the outcomes of the proposed models. The results of these studies show that the model ASAE-DNN was 97% accurate.

Keywords: Adapted Stacked AutoEncoder, diabetic retinopathy , deep learning and Deep Neural Network.

I. INTRODUCTION

One of the most advanced organs, the human eye is retinal, pupil, iris, lens and optical nerve. Appears as an effective screening method for early detection for eye disease automated retinal image analysis. Retinopathy (DR) and glaucoma, uncontrolled diabetes, can lead to blindness. Diabetes mellitus is elevated blood glucose chronic condition due to either insulin shortage or resistance to insulin [1,2].

The worldwide diabetes prevalence was found at around 425 million in 2017 and is expected to increase to about 630 million in 2045 [3]. In India, about a fifth to a third (57 million) of all people with Diabetes Mellitus (DM) will have retinopathy by 2025. Amongst them, about 5.7 million diabetes sufferers will suffer from extreme retinopathy and will need a laser or surgical operation to maintain vision [4].

Convolutional Neural Networks (CNNs), a deep learning branch, has an outstanding performance of applications such as medical imaging and analysis of images. This work provides the two-stage DR detection method based on the model with retinal images with these motives. At first, the image data of MESSIDOR is used as an input. In the model

ASAE-DNN, the DNN-based system is used with DR classification Adapted Stacked Automobile Encoders (ASAE-DNN).

The rest of the paper is written like this. Section 2 deals with the classification of DR related plays. Section 3 describes the methods proposed for defining the DR classification with ASAE-DNN. Section 4 discusses the experimental findings. Section 5 includes the conclusion and prospective work.

II. RELATED WORK

A good computer-aided clinical decision support system was developed to identify retinal images using the neural network and introduced [5]. The literature proposed different methods for the identification of DR. With and without moderate retinopathy, and Bayesian ANN has been educated to distinguish between healthy and diabetic eyes [6]. The proposed methodology to modelling based on m -medios [7] was extended and combined with a Gaussian model of a mixture in an ensemble to constructing a hybrid level classification to enhance grade accuracy.

A new automated screening scheme is proposed to support diabetic retinopathy [8] which involves the automatic selection,

screening and classification of colour fundus pictures of diabetic retinopathy that might help diagnose and control diabetic retinopathy.

A novel automated identification with the use of fluid image processing techniques for diabetic retinopathy and maculopathy with eye-fundus images [9]. The Machine Learning Bagging Ensemble Classifier (ML-BEC) is designed to classify retinal features for DR disease diagnosis and early detection using computer teaching and ensembling methods [10]. A comprehensive deep learning algorithm based on data was designed and evaluated as a new DR detection diagnostic tool [11].

III. PROPOSED METHODOLOGY

Figure 1 displays the overall design of the Adapted Auto-Encoder stack for Diabetic retinopathy with a Deep neural network. The network uses an image data MESSIDOR as input on the first level and generates a low-level fixed-length function vector from the input. No function engineering is necessary, and the extractor immediately learns in the secret layer, contrary to several traditional DR methods. The ASAE-DNN extracts the data collection with ASAE and classifies the dataset with softmax row. Then, three hidden layers cross the low-level feature vector, and softmax has been used to measure the diabetic retinopathy classification result. During the following supervised training step, the final classification layer (output layer) is applied to practice the final Diabetic Retinopathy predictive models.

3.1. Input MESSIDOR dataset

In this work, to identify DR, a benchmark MESSIDOR dataset was used [12]. This data had approximately 1200 colour fundus images with proper annotation. The images in the dataset were categorized into four categories. Image grading was performed on the existence of microaneurysms, and hemorrhages were allocated to the images. The image without any symptoms indicates healthy retina. The image which has some microaneurysms represents stage 1 (Mild) whereas the image with some microaneurysms as well as hemorrhages denotes stage 2 (Moderate). The images that

indicate more microaneurysms, as well as hemorrhages that are placed under stage 3 (Severe).

3.2. Diabetic Retinopathy classification Using ASAE-DNN model

Motivated by the fascinating features of deep networks, this work proposes an examination of the entire classification problem using DNN-based structures using adapted stacked autoencoders (ASAE-DNN). The DNN diabetes dataset classifier is built with an adapted autoencoder stacked with three hidden layers of extraction, and the last hidden layer to the classification process is attached to the softmax layer. The output layer gives the

probabilities for a specific record in the diabetic and non-diabetic groups.

Consider an ASAE network with three layers, let $l = 1, 2, \dots, n$ signifies the raw input of MESSIDOR images also I' is the reconstruction of the image as well as $w^{(l,1)}, w'^{(l,1)}, b^{(l,1)}, b'^{(l,1)}$ that are the weights and bias terms for the l th layer encoder and decoder, individually, $l = 1, 2, 3$. Primarily, the SAE maps the input image keen on a hidden design hid as signified in equation (1)

$$\sum_{i=1}^n \sum_{l=1}^3 hid_i^{(l)} = \sum_{i=1}^n \sum_{l=1}^3 f(I_i'^{(l)}) \quad (1)$$

$$f(I_i'^{(l)}) = s_f(w^{(l,1)} I_i'^{(l)} + b^{(l,1)})$$

Then the latent representation $hid(l)$ mapped back into a reconstruction $\mathbb{R}$ from a corrupted version I' as in Eq.(2)

$$\mathbb{R} = g\left(\sum_{i=1}^n \sum_{l=1}^3 hid_i^{(l)}\right)$$

$$g(I^l) = s_g(w'^{(l,1)} \sum_{i=1}^n \sum_{l=1}^3 hid_i^{(l)} + b'^{(l,1)}) \quad (2)$$

where s_f and s_g stand nonlinear activation function. The cost function for SAE well-defined through the reconstruction error $\mathbb{R}(I', \mathbb{R})$ between original input I' and reconstruction $\mathbb{R}$ as in equation (3):

$$J_{ASAE} = \sum_{l=1,2,3} \mathbb{R}\left(I'^{(l)}, g\left(\sum_{i=1}^n \sum_{l=1}^3 f(I_i'^{(l)})\right)\right) \quad (3)$$

Where $\mathbb{R}(I', \mathbb{R}) = \|I' - \mathbb{R}\|^2$. Moreover, sparsity constraints term $\mathbb{T}$ is added into hidden units of ASAE to improved learning features, and an additional penalty term is introduced into the objective function in equation (4). Then and there the new cost function of ASAE can be rewritten as in equation (4):

$$J_{MSAE}(\theta) = J_{ASAE} + \mathbb{W} \sum_{j=1 \text{ to } m} KL(\mathbb{T} \parallel \mathbb{A}_j) \quad (4)$$

The additional penalty terms Kullback–Leibler divergence (KL) in equation (5) is well-defined by the cross-entropy in the middle of $\mathbb{T}$ and $\mathbb{A}_j$.

$$KL(\mathbb{T} \parallel \mathbb{A}_j) = \sum_{j=1}^m \mathbb{T} \log \frac{\mathbb{T}}{\mathbb{A}_j} + (1 - \mathbb{T}) \log \frac{1 - \mathbb{T}}{1 - \mathbb{A}_j} \quad (5)$$

$$\mathbb{A}_j = \frac{1}{k} \sum_{i=1}^k h_i$$

Here, $\mathbb{T}$ designate the target sparsity level, $\mathbb{A}_j$ denotes the average activation rate for the j th unit, m remains the number of hidden units, $\mathbb{W}$ stands the weight for penalty terms. The sparsity ditions code for each layer represents the input data in the quest for a collection of over-complete base vectors to achieve a better image function. The intrinsic feature of an image is learned by a three-layer

scattered coding process, as the sparse representation at pixel level created the feature. Cascading with the softmax classifier is possible to construct a deep network classifier through stacking an autoencoder. Stacked auto encoder may have two or more layers of auto encoders. Let $\{I_1, \dots, I_n\}$ variables be $\{Y_1, \dots, Y_n\}$ input vector given as input to DNN besides the corresponding output class, here $n = 3$. The training method aims to change the DNN parameters to know the input vectors to identify the appropriate output with greater accuracy if the input vectors for the training are assumed. The instructional classification procedure ASAE-DNN is as described in the following:

1. The first autoencoder layer is typically achieved with the original input vector $\{I_1, \dots, I_n\}$ such as the same vector as the destination. This layer tries to recreate the input by removing the $\{\mathcal{F}_{(1,1)}, \dots, \mathcal{F}_{(1,i)}\}$ functions.

2. In addition to yielding the output vector of the first autoencoder layer $\{o_{(1,1)}, \dots, o_{(1,i)}\}$ as an input vector, the second autoencoder layer is equipped by enchanting the output vector as input vector and generates an output vector $\{o_{(2,1)}, \dots, o_{(2,j)}\}$. The second autoencoder layer attempts to recreate the input $o_{(1,i)}; i = 1, 2, \dots, C$.

3. The third autoencoder layer is equipped by deciding to take the output vector as the input vector and generates the output vector of the second autoencoder layer $\{c_{(2,1)}, \dots, c_{(2,j)}\}$ as the input vector and generates the output vector $\{c_{(3,1)}, \dots, c_{(3,k)}\}$. The third layer of autoencoders attempts to recreate the $o_{(2,j)}; j = 1, 2, \dots, R$ data.

4. The stacked autoencoder is cascaded via SVM with the softmax classifier layer [13] which will increase the accuracy of DNN classification. This layer is trained through taking output of the third autoencoder layer, $c_{(3,k)}; k = 1, 2, \dots, U$ as the input vector and the original class variables $\{Y_{(1)}, \dots, Y_{(N)}\}$ as the query sequence from the training data.

5. Eventually, backpropagation would be used which called fine is tuning, improving the efficiency of the DNN classification. The network is made redundant in some kind of controlled manner with the training data. Once the first hyperplane classification is defined by a back propagation algorithm, the training process is terminated whether it is local or global optimum. The SVM classification hyperplanes are suitable globally by using a comprehensive risk minimisation framework.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the proposed ASAE-DNN is evaluated in this section, and the performance results are compared with existing Neural Network [4], ML-BEC [9] and deep learning

[10] schemes. The performance measurement is done in terms of precision, f-measurement, recall and accuracy.

Precision: It reflects the proportion of positive samples correctly classified as expected in equation (5):

$$Precision = \frac{TP}{FP+TP} \quad (5)$$

Recall: The recall of a classifier reflects the positive samples properly assigned to the total number of positive samples and is calculated as in equation (6):

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

F-measure: this is also referred to as F 1-score, and as in equation (7) is the harmonic mean of precision and recall:

$$F - measure = \frac{2*(Recall * Precision)}{(Recall + Precision)} \quad (7)$$

Accuracy: This is one of the most frequently used performance classification measures and is defined as a ratio between the correctly classified samples and the total number of samples as in equation (8):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

Where true positive (TP) samples are properly classified as no DR, false positive (FP) samples are incorrectly classified as DR, True negative (TN) samples are properly classified as DR, and false negatives (FN) are incorrectly classified as DR.

4.1. Precision Rate comparison

Figure 2. Representation of Precision Comparison

From the above Figure 2, the graph shows how accurate the number of images in the specified datasets is compared. These methods are implemented as Neural Network, ML-BEC and deep learning and ASAE-DNN. When the number of records increases according to the precision value, from this graph, it is learned that the proposed ASAE-DNN offers 94% higher precision than previous methods that yield better results in the

classification of CR due to adapted stacked autoencoder. The numerical results of Precision Comparison is shown in Table 1.

Table 1. The numerical results of Precision Comparison

No.of images	Neural Network	ML-BEC	deep learning	ASAE-DNN
100	79	82	85	87
200	82	85	87	89
300	83	87	89	92
400	85	89	90	93
500	89	90	91	94

4.2. Recall comparison

Figure 3. Representation of Recall Comparison

From the above Figure 3, the graph illustrates the recall relation for the number of images in the listed datasets. These methods are implemented as Neural Network, ML-BEC and deep learning. Increasing the number of images often increases the correct value for the recall. Through this graph, it is discovered that the current ASAE-DNN offers recall 95% higher than previous methods. The explanation for this is that the ASAE-DNN extracts the features directly, which will enhance the detection and classification of DR. The numerical results of Recall Comparison is shown in Table 2.

Table 2. The numerical results of Recall Comparison

No.of image s	Neural Networ k	ML- BE C	deep learnin g	ASAE -DNN
100	88	89	90	91
200	89	90	91	92
300	90	91	92	93
400	91	92	93	94
500	92	93	94	95

4.3. F-measure Rate comparison

From the above Figure 4, the graph explains the f-measure relation for the number of images in the given datasets. These methods are implemented as Neural Network, ML-BEC and deep learning.

Figure 4. Representation of F-measure Comparison

When the number of data is increased, and the f-measure value is increased accordingly. From this graph it is learned that the proposed ASAE-DNN offers 95% higher f-measurement than previous methods. Therefore the proposed ASAE-DNN algorithm is stronger than the current algorithms in terms of better performance of classifying DR. The numerical results of F-measure Comparison is shown in Table 3.

Table 3. The numerical results of F-measure Comparison

No.of images	Neural Network	ML-BEC	deep learning	ASAE-DNN
100	84	85	87	89
200	85	87	89	91
300	87	89	91	93
400	89	90	92	94
500	90	91	93	95

4.4. Accuracy comparison

From the above Figure 5, the diagram illustrates the processing time relation for the number of images in the specified datasets. These methods are implemented as Neural Network, ML-BEC and deep learning and ASAE-DNN. From this graph, it is known that the proposed ASAE-DNN algorithm is higher than the existing algorithms with a high precision rate of 97% in terms of better template matching results. This is due to the automatic extraction of the function in the ASAE-DNN algorithm, which increases the DR classification results. The numerical results of Accuracy Comparison is shown in Table 4.

Figure 5. Representation of Accuracy Comparison

Table 4. The numerical results of Accuracy Comparison

No.of images	Neural Network	ML-BEC	deep learning	ASAE-DNN
5	85	87	89	90
10	87	89	90	91
15	89	90	91	92
20	90	91	93	95
25	91	92	93	97

V. CONCLUSION AND FUTURE WORK

This study proposes that ASAE-DNN algorithms use stacked auto-encoders, and that three hidden layers be used for extraction of features accompanied by a softmax classifier classification for DR classification with a high accuracy rate of 97%. It provides a reliable solution for DR detection within a large-scale data set, as well as the results achieved indicate the good efficiency of today's computer-aided model in providing efficient, low-cost and objective DR diagnostics without any need for clinicians to manually examine and grade images. In the future, it may also be important to investigate different types of common patient metadata, such as genetic factors, patient history, duration of diabetes, hemoglobin A1C value, and other clinical data that may influence a patients at risk of retinopathy. Introducing this information to the classification model could give informative correlations to following DR risk factors from outside strictly imaging information, increase thermal diagnostic accuracy.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

HUMAN AND ANIMAL RIGHTS

No animals/humans were used for studies that are basis of this research.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The authors confirm that the data supporting the findings of this research are available within the article.

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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