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Diabetic Retinopathy using Lstm-Rnn

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Abstract: Diabetic retinopathy is an significant cause of loss of vision and blindness in millions of people worldwide. While screening protocols-fluorescence and optical accuracy to the identification of the disease, in most cases-have been identified, the patients remain unaware, and they can't perform these tests on time. The early diagnosis of the condition plays a vital role in preventing loss of vision which results in a prolonged period of untreated diabetes mellitus between patients. Different profound learning strategies were applied for classification and disease prediction in diabetic retinopathy datasets, but most of them ignoreddata pre-processing and dimension reduction and resulted in partial outcomes. The diagnostic analysis is carried out in this paper with the use of profound learning and the LSTM-RNN methodology in this manner and by segmentation through Fuzzy c. Output indicates that the whole system being tested is validated by the use of 400 MESSIDOR (database) retinal fundus images.

Keywords : Deep learning, FCM, RNN, LSTM etc.

I. INTRODUCTION

According to the WHO, over 347 million people suffer from diabetes and by 2030 it could become the world's 7th largest cause of death. Diabetes patients appear to have an abnormality of retina over the years because of the emerging challenge called DR. Diabetes patients above the age of 30, with 78% chance of having DR[1]. [3]. DR is attributed to diabetic mellitus ' long-term status. Blood vessels are blocked, leaking and expand arbitrarily[2] as a result, retinopathy means damage to the retina. DR is asymptomatic; it does not affect vision until it progresses. Therefore, DR screening is important for type1 patients (insulin dependent) and type2 patients (non-insulin dependent), as the diabetic retinopathy in all forms is at risk. The DR has two stages, NPDR and Proliferative Rethinopathy (PDR). DR has two stages. Late retinopathy is NDPR. At this point, the size of blood vessels diminishes, the like of balloons expand and retinal blood vessels (RBV) start to leak at retinal fluid. PDR is retinopathy's advance process. An irregular RBV bleeds into vitreous at this point. Therefore, ruptured blood vessels can form the scar tissue that can tug on the retina contributing to retinal detachment. The purpose of the paper is to establish a method for recognizing retinal color fundus representations patients with DR.

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Color fundus pictures are widely used for early retinopathy diagnosis. Figure 1 provides an picture of the Visual Retinal Color Fundus. The different disease symptoms of diabetic retinopathy include microaneurysm, retinal haemorrhages, rough exudates and cotton wools. We emphasis in this report on early identification of diabetes retinopathy in fundus photos. In this paper we consider microaneurysms. Microaneurysms are the first significant symptom of diabetic retinopathy, small red spots on the retina. Doling of the vein of the amygdala is the first symptom of DR. Late improvements can take place, leading to occlusion, as well. This causes tiny bulges, called a microaneurysm, in vascular walls.
The identification of diabetic retinopathy involves three steps-color fundus vision analysis, the retrieval of diagnostic functions and the recognition of DR.

Fig. 1 Sample digital color fundus image

Becoming lit by medical pictures, low contrast and noise. A variety of methods to identify DR using a simulated color fundus picture are proposed. A prepared picture is required for both methods. In order to improve the contrast, the preprocessing of fundus picture is carried out. Extracting functionality plays an significant function in machine vision. For the preparation of classifier parameters, derived features are included. A assisted vector machine (SVM) shall be used to identify diabetics retinopathy. SVM minimizes the upper limit of the error by optimizing the margin between the planes and results. SVM's classification has been successful. This can be used for regression as well. Lagrange and quadratic programming optimization were accomplished. Blindness and vision impairment for working age people in developing countries. Diabeticretinopathy. To order to prevent more vision loss for people with diabetes, early diagnosis and regular screening is important. Taking into account the increasingly growing number of diabetic patients, automated DR ranking will decrease ophthalmologists ' workload, improve productivity and minimize DR screening costs. The blood-retinal membrane breaks down and releases plasma proteins, lipids and calcium from the veins. This is due to exudations. The precise and automated detection of exudate is therefore essential to the treatment of DR. Exudates are portrayed in color fundus images, with varying shapes and contrast, as white or yellow luminous structures.

Various methods have been suggested for automated identification of exudate. The identification of exudates can usually be divided into 3 separate steps: exudation, isolation and machine learning. Different algorithms for the extraction of exudate candidates have been developed, including morphological operating approaches, clustering approaches and pixel dependent machine learning.

Generally, extraction technologies and machine learning are used to further identify candidates after they have obtained their exudate candidates. Zhang et al. obtained 28 features including strength, geometrical and texture based attributes, and random forests for classification purposes, for all candidates, which included multi-layer perceptron, radial basis function, and the support vector machine Fo and other characteristics.

In this paper we merged the image processing steps with deeper neural networks to enhance the precision of the identification of exudates at pixel level. The final opening algorithm is used to get the applicants for the exudates. Afterwards, the field around the seeds is stripped and passed for classification to qualified neural convolutionary networks. Accurate exudate identification at pixel level is then done.

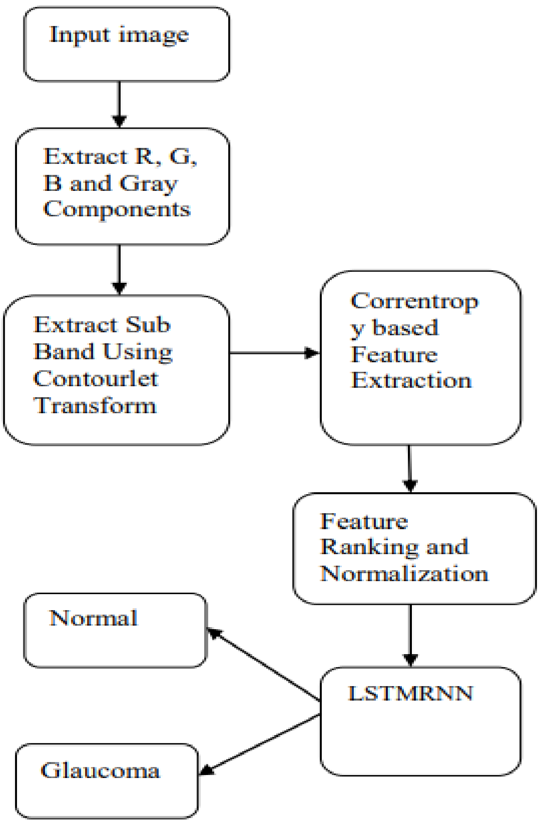

Fig. Automatic detection of glaucoma using LSTM-RNN

Deep Learning

Deep learning is an artificial intelligence system imitating the activity of the brain in the processing of data. Profound education is a branch of artificial intelligence (AI) computer education that has networks and can learn from unstructured or non-labeled data without supervision. Sometimes known as profound neural learning or profound neural network. The digital era that brought an avalanche of data of all sizes and from all areas of the world has contributed to deep awareness. This material, which is commonly known as big data, comes from outlets such as social media, Web search, e-commerce websites and online cinemas. This tremendous amount of knowledge can be easily accessed and exchanged via Fintech applications such as cloud computing. Nevertheless, records, which are typically unstructured, are so vast that people can comprehend and retrieve the related information for decades. Organizations understand the unbelievable opportunity that this abundance of knowledge will bring and adapt more and more for automated assistance of AI systems.

Example

You may construct a profound learning example using the above-mentioned fraud detection method with machine learning. When the learning tool generates a representation of the parameters that a user sends or receives about the amount of dollars, the learning process will begin building on the effects of machine learning.

Layer is based on the previous layer with additional data, including manufacturer, sender, recipient, social media incident, credit rating, IP address and a variety of other features that can take years for a person to communicate with. Deep learning algorithms are trained not only to generate patterns from any event, but also to know when a pattern means that a fraudulent investigation is required. The end layer sends a signal to an investigator who can suspend the account of the customer until all unfinished work is done. Profound thinking is used for a variety of activities in all sectors. Few examples of profound learning integration include commercial applications using image recognition, open source platforms with user advising applications, and medical research resources which explore reuse drugs for new conditions.

II. PROPOSED METHODOLOGY AND TECHNOLOGY

The classification of diagnostic tasks is carried out in this method by way of profound learning and the LSTM-RNN methodology and the use of Fuzzy c tools. The performance will be shown by the assessment and testing of the entire suggested system with 400 MESSIDOR retinal fundus images (database). A traditional CNN is organized in many layers such as transmission networks. As separate from the forwarding LSTM-RNN stream, a sub-sampling segment may contain many convolutionary layers. This multi-layer system uses completely integrated structures. LSTM-RNN is modelled from a general perspective for the processing and simple handling of two-dimensional pictures in research activities. For faster image processing, LSTM-RNN allows local links of different weights. This implies that, with lower training cycles, LSTMs can obtain parameters.

FCM

FCM clustering was used to achieve the local dynamic threshold of each subimage, together with the global threshold matrix for color retinal segment images.

Retinal Image Segmentation Using FCM.

- In conjunction with the global threshold based on the FCM clustering, this defines the images segmentation process using the hierarchical threshold:

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2. The retinal image has been broken into a set of sub-images (K subimages). The FCM algorithm was used by means of fuzzy memberships to assign pixels to various groups in each subimage. FCM is an iterative optimization which reduces the cost function as defined:

$$J(U,V) = \sum_{i=1}^{n}\sum_{k=1}^{c}(u_{ki})^{m}\|x_i - v_k\|^2$$

The clustering node of the kth cluster is Uki reflecting the membership of Pixel Xi within the kth cluster and Vk. Provided that the gray size magnitude was used as the main attribute for a clustering, the center line midpoint was used as the segmentation threshold where the mean of the two clustering centers was used as the subimage threshold.
In order to attain the global threshold and to create the global matrix S of the same size as the original frame, the entire original retinals were categorized in the same manner as above.
If the thresholds of the respective sub-images were interpolated to the same size dynamic threshold matrix D as the whole original image, a mean size filter 10 to 10 was used for matrix D.
The final matrix T threshold was established as

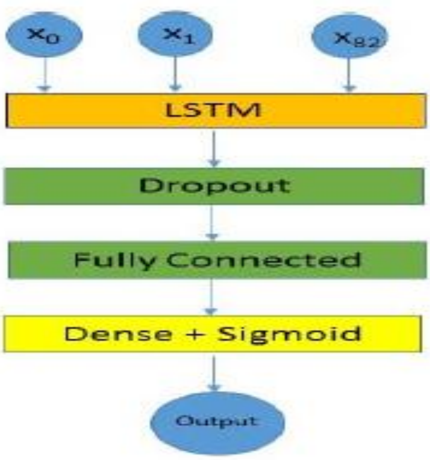
$$T = kS + (1-k)\,D$$

where the value of *k* was set to 0.1.

By comparing the T-threshold matrix to the retinal image, the segmentation result was obtained. The subimage's scale influences the segmentation effects of retinal images. The figure displays the effects of the FCM clustering for various sizes. The scale of 30* 40 pixels has been chosen as the most appropriate subimage size based on both the running time and the accuracy of the local threshold.

Lstm Deep Learning Model

LSTM is an RNN sort in which other nodes in the same layer are linked to boost learning with the removal and retrieval of relevant knowledge. The LSTM model flow graph is shown in the diagram. The first LSTM 128 kernel layer is a default adam layer with a 0.5 limit. The second layer is a custom layer. Dropout layer output is connected to a completely connected layer which provides a thick layer input with sigmoid feature in order to distinguish attack normal data.



- **Fig. LSTM Deep Learning Model Architecture**

III. Future Scope

This study demonstrated a better method for detecting diabetic retinopathy by calculating accurately the number of microaneurysms and their location. The importance obtained of sensitivity and precision indicates that for non-proliferative diabetic retinopathy diagnosis, the new diagnostic method is stronger. A proliferating diabetic retinopathy sensing device is to be identified in this document by taking the color fundus photos as featuring cotton wools and enlarged blood vessels. The DR detection system may be applied to a multi-class classification of diabetic retinopathy, namely by using deep learning to classify into stable, moderate not proliferative, extreme nonproliferative and proliferative diabetic retinopathy.

IV. Tool Used

Python is a language of general comprehension, high-level programming. Python's architecture theory, developed by Guido Van Rossum and first published in 1991, stresses the preparation of code through the use of broad whitespace. The language models and object-oriented methodology was developed to help programmers build simple, functional code for projects of large size and small scale.

Typing and storing waste efficiently is Python. It follows various paradigms of programming, including procedural, objective and functional programming. Thanks to the robust standard library Python is also defined as "batteries included."

V. RESULT

Training

Train on 330 samples, validate on 83 samples
Epoch 1/10
330/330 [==============================] - 11s 34ms/step - loss: 0.7355 - acc: 0.5394 - val_loss: 0.7824 - val_acc: 0.4096
Epoch 2/10
330/330 [==============================] - 3s 9ms/step - loss: 0.5742 - acc: 0.7182 - val_loss: 1.4167 - val_acc: 0.1446
Epoch 3/10
330/330 [==============================] - 3s 9ms/step - loss: 0.4034 - acc: 0.8061 - val_loss: 0.6632 - val_acc: 0.6627
Epoch 4/10
330/330 [==============================] - 3s 9ms/step - loss: 0.2845 - acc: 0.8727 - val_loss: 1.9088 - val_acc: 0.2892
Epoch 5/10
330/330 [==============================] - 3s 9ms/step - loss: 0.2207 - acc: 0.9121 - val_loss: 1.5190 - val_acc: 0.4699
Epoch 6/10
330/330 [==============================] - 3s 9ms/step - loss: 0.1188 - acc: 0.9576 - val_loss: 2.4988 - val_acc: 0.3012
Epoch 7/10

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330/330 [==============================] - 3s 10ms/step - loss: 0.0490 - acc: 0.9848 - val_loss: 3.6466 - val_acc: 0.2892
Epoch 8/10
330/330 [==============================] - 3s 10ms/step - loss: 0.0354 - acc: 0.9909 - val_loss: 1.7496 - val_acc: 0.5301
Epoch 9/10
330/330 [==============================] - 3s 10ms/step - loss: 0.0297 - acc: 0.9939 - val_loss: 1.9168 - val_acc: 0.4819
Epoch 10/10
330/330 [==============================] - 3s 9ms/step - loss: 0.0175 - acc: 0.9939 - val_loss: 2.5069 - val_acc: 0.4096

Testing

103/103 [==============================] - 0s 2ms/step
score: [1.3940480287792614, 0.5825242721340032]
(103, 1)
[[0.0], [1.0], [0.0], [1.0], [0.0], [0.0], [0.0], [1.0], [1.0], [1.0], [1.0], [0.0], [1.0], [1.0], [0.0], [0.0], [1.0], [0.0], [0.0], [0.0], [1.0], [0.0], [0.0], [1.0], [1.0], [1.0], [1.0], [1.0], [0.0], [1.0], [0.0], [0.0], [0.0], [0.0], [0.0], [0.0], [1.0], [1.0], [1.0], [0.0], [1.0], [1.0], [0.0], [0.0], [0.0], [1.0], [0.0], [0.0], [1.0], [0.0], [0.0], [1.0], [1.0], [0.0], [0.0], [1.0], [1.0], [1.0], [1.0], [0.0], [1.0], [1.0], [1.0], [0.0], [1.0], [1.0], [0.0], [0.0], [1.0], [1.0], [1.0], [1.0], [1.0], [1.0], [1.0], [0.0], [1.0], [1.0], [0.0], [1.0], [0.0], [1.0], [0.0], [1.0], [0.0], [0.0], [1.0], [1.0], [1.0], [1.0], [1.0], [1.0], [1.0], [1.0], [0.0], [0.0], [0.0], [0.0], [1.0], [0.0], [1.0], [0.0], [1.0]]
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]

	precision	recall	f1-score	support
0	0.52	0.53	0.53	45
1	0.63	0.62	0.63	58
accuracy			0.58	103
macro avg	0.58	0.58	0.58	103
weighted avg	0.58	0.58	0.58	103

[[24 21]
[22 36]]
24 21 22 36
sensitivity: 0.6206896551724138
specificity: 0.5333333333333333

VI. CONCLUSION

This thesis presented an improved scheme for the detection of diabetic retinopathy by accurate determination of number and area of microaneurysm. The achieved value of sensitivity and specificity shows that the proposed diagnostic system is better for non-proliferative diabetic retinopathy detection. Future work of this paper is to propose a proliferative diabetic retinopathy detection system by considering cotton wools and abnormal blood vessels as features from color fundus images. DR detection system could be extended to multi class diabetic retinopathy classification, namely to classify into healthy, mild non-proliferative, moderate non-proliferative, severe non-proliferative, and proliferative diabetic retinopathy by using deep learning.

REFERENCES

1. Sohini Roychowdhury ; Dara D. Koozekanani ; Keshab K. ParhiAutomated detection of neovascularization for proliferative diabetic retinopathy screening2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).
2. Shailesh Kumar ; Basant KumarDiabetic Retinopathy Detection by Extracting Area and Number of Microaneurysm from Colour Fundus Image2018 5th International Conference on Signal Processing and Integrated Networks (SPIN).
3. Shuang_Yu ; Di_Xiao ; Yogesan_Kanagasingam_"Exudate detection for diabetic retinopathy with convolutional neural networks2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).
4. Xu Jin ; Hu Guangshu ; Huang Tianna ; Huang Houbin ; Chen BinThe Multifocal ERG in Early Detection of Diabetic Retinopathy2005 IEEE Engineering in Medicine and Biology 27th Annual Conference.
5. Morium Akter ; Mohammad Shorif Uddin ; Mahmudul Hasan KhanMorphology-based exudates detection from color fundus images in diabetic retinopathy2014 International Conference on Electrical Engineering and Information & Communication Technology.
6. Z. A. Omar ; M. Hanafi ; S. Mashohor ; N. F. M. Mahfudz ; M.Muna'imAutomatic diabetic retinopathy detection and classification system2017 7th IEEE International Conference on System Engineering and Technology (ICSET).
7. Haniza Yazid ; Hamzah Arof ; Norrima MokhtarEdge sharpening for diabetic retinopathy detection2010 IEEE Conference on Cybernetics and Intelligent Systems.
8. Ömer Deperlıoğlu ; Utku Köse Diagnosis of Diabetic Retinopathy by Using Image Processing and Convolutional Neural Network.
9. Büşra Yaşar ; Bartu Yeşilkaya ; Özlem Karabiber Cura ; Aydın Akan A New Method to Detect Diabetic Retinopathy2018 Medical Technologies National Congress (TIPTEKNO).
10. Kranthi Kumar Palavalasa ; Bhavani SambaturuAutomatic Diabetic Retinopathy Detection Using Digital Image Processing2018 International Conference on Communication and Signal Processing (ICCSP).

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