Detection of Diabetic Retinopathy Using CNN

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Abstract- *In this paper, Diabetic retinopathy is a leading problem throughout the world and many people are losing their vision because of this disease. The disease can get severe if it is not treated properly at its early stages. The damage in the retinal blood vessel eventually blocks the light that passes through the optical nerves which makes the patient with Diabetic Retinopathy blind. Therefore, in our research we wanted to find out a way to overcome this problem and thus using the help of Convolutional Neural Network (ConvNet), we were able to detect multiple stages of severity for Diabetic Retinopathy. There are other processes present to detect Diabetic Retinopathy and one such process is manual screening, but this requires a skilled ophthalmologist and takes up a huge amount of time. Thus our automatic diabetic retinopathy detection technique can be used to replace such manual processes and the ophthalmologist can spend more time taking proper care of the patient or at least decrease the severity of this disease.*

I. INTRODUCTION

Diabetic retinopathy is considered the major reason that causes blindness among working increased to 552 million people in 2030. The person who has diabetes is at high risk of eyes disease; include DR diabetic retinopathy, Diabetic Macular Edema (DME) glaucoma and cataract. To process this information, the brain needs to light signal to penetrate the eyes through the shape on the retina and lenses. This process can be disturbed easily by different diseases which prevent the correct explication of a visual signal, and this disorder is DR diabetic retinopathy which is an accompanying disorder of diabetes disease. According to early detection of DR diabetic retinopathy, the process of eyes injury might be slow down and even stopped surgically, while without any treatments it will be caused irreversible damage and blindness in advanced stages. Therewith, the process of retinal detection is difficult manually and spend time-consuming, so the system that can be analyzed the retina automatically and observe the development of disease will highly help both patients and ophthalmologists.

Recently, deep learning has been enhanced to the purpose of computer vision in diagnostic and classification of images and is the key device has been used to automate a task in people life.

The Convolution Neural Networks CNN consistently have been developed to detect the objects, segmentation and classification. CNN is a class of artificial neural networks that are proven to be highly effective in cases like image classification and recognition. CNN has been successful used in analyzing visual imagery, identifying persons and objects. Furthermore, CNN has been used effectively to solving various medical image problem.

CNN is one of the important methods to fix an automatic analysis of retinal images. The CNNs is used to classified retinal injury to an appropriate degree and also to extract features of retinal damage. Many studies are focusing on the anomalies ordinarily known as (Exudates) or light lesions. Another way to assess entire retinal images is labelled then as a suitable degree of diabetic retinopathy. For this process, they use different image pre-processing ways to extract several important features and classified to their particular classes. And can by implementing CNNs to detect the five degrees of retinal damage DR. At last, use the specificity, accuracy, sensitivity, (ROC) Receiver Operating Characteristic and (AUC) Area Under Curve for performance evaluation the proposed models .

In addition, can get the best publicavailable datasets of images to train for its models. This paper aims to review the most important recent studies about using CNN to detect DR, as well as to present the importance of this algorithm and how to use this technique for DR detection efficiently.

II. LITERATURE SURVEY

2.1 Application of higher order spectra for the identification of diabetes retinopathy stages.

Feature extraction based classification and DL has been used to classify DR. In Acharya et al. [18] higher order spectra technique was used to extract features from 300 fundus images and fed to a support vector machine classifier; it classified the images into 5 classes with sensitivity of 82% and specificity of 88%. Different algorithms were developed to extract DR lesions such as blood vessels, exudates, and micro aneurysms [19]. Exudates have been extracted for DR grading [20 - 24]. Support vector machine was used to classify the DIABETDB1 dataset into positive and negative classes using area and number of micro aneurysms as features.

2.2 Rethinking the inception architecture for computer vision

Feature extraction based classification methods need expert knowledge in order to detect the required features, and they also involve a time consuming process of feature selection, identification and extraction. Furthermore, DL based systems such as CNNs have been seen to outperform feature extraction based methods [26]. DL training for DR classification have been performed in two major categories: learning from scratch and transfer learning.

2.3 Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs.

A convolutional neural network (CNN) was trained to classify a dataset of 128,175 fundus images into 2 classes, where the first class contains images with severity levels 0 and 1, and the second class contains levels 2, 3 and 4 [27]. In an operating cut point picked for high sensitivity, [27] had a sensitivity of 97.5% and specificity of 93.4% on the EyePACS-1 dataset which consists of 9963 images; it scored a sensitivity of 96.1% and a specificity of 93.9% on the Messidor-2 dataset; and in an evaluation cut point selected for high specificity, the sensitivity and specificity were 90.3% and 98.1% on the EyePACS-1, while 87% and 98.5% was scored on the Messidor-2, consecutively.

2.4 Convolutional neural networks for diabetic retinopathy

Using a training dataset of over 70,000 fundus images, Pratt et al. [28] trained a CNN using stochastic gradient descent algorithm to classify DR into 5 classes, and it achieved 95% specificity, 75% accuracy and 30% sensitivity. A DL model was trained from scratch on the MESSIDOR-2 dataset for the automatic detection of DR in [29], and a 96.8% sensitivity and 87% specificity were scored.

2.5 Automated identification of diabetic retinopathy using deep learning

A CNN was trained from scratch to classify fundus images from the Kaggle dataset into referable and non-referable classes, and it scored a sensitivity of 96.2% and a specificity of 66.6% [30]. A dataset of 71896 fundus images was used to train a CNN DR classifier and resulted in a sensitivity of 90.5% and specificity of 91.6% [31]. A DL model was designed and trained on a dataset of 75137 fundus images and resulted in a sensitivity and specificity scores of 94% and 98%, respectively.

2.6 Comparative Study of Fine-Tuning of Pre-Trained Convolutional Neural Networks for Diabetic Retinopathy Screening

In order to avoid the time and resource consumed during DL, Mohammadian et al. [33] fine-tuned the Inception-V3 and Exception pre-trained models to classify the Kaggle dataset into two classes. After using data augmentation to balance the dataset, [33] reached at an accuracy score of 87.12% on the Inception-V3, and 74.49% on the Exception model.

III. EXISTING SYSTEM

In the paper, they developed a network with CNN architecture and data augmentation which can identify the intricate features involved in the classification task such as micro-aneurysms, exudate and hemorrhages on the retina and consequently provide a diagnosis automatically and without user input. Network was trained using a high-end graphics processor unit (GPU) on the publicly available Kaggle dataset and demonstrate impressive results, particularly for a high-level classification task. On the data set of 80,000 images used our proposed CNN achieves a sensitivity of 95% and an accuracy of 75% on 5,000 validation images. The structure of our neural network, shown in below was decided after studying the literature for other image recognition tasks. Structure of neural network for image recognition Increased convolution layers are perceived to allow the network to learn deeper features. The first layer learns edges the deepest layer of the network, the last convolutional layer, should learn the features of classification of DR such as hard exudate.

IV. PROPOSED SYSTEM

The diagnosis of diabetic retinopathy (DR) through colour fundus images requires experienced clinicians to identify the presence and significance of many small features which, along with a complex grading system, makes this a difficult and time consuming task. In this paper, we propose a CNN approach to diagnosing DR from digital fundus images and accurately classifying its severity. We developed a network with CNN architecture and data augmentation which can identify the intricate features involved in the classification task such as micro-aneurysms, exudate and hemorrhages on the retina and consequently provide a diagnosis automatically and without user input. On the data set of 80,000 images used our proposed CNN achieves a sensitivity of 95% and an accuracy of 75% on 5,000 validation images.

IV. SYSTEM ARCHITECHTURE

In this the main images are got from the kiggle dataset so that the work of the CNN algorithm is to train the images and to detect the image about the diabetic retinopathy. If the image is found to be have diabetic retinopathy then it would aleart for the user.

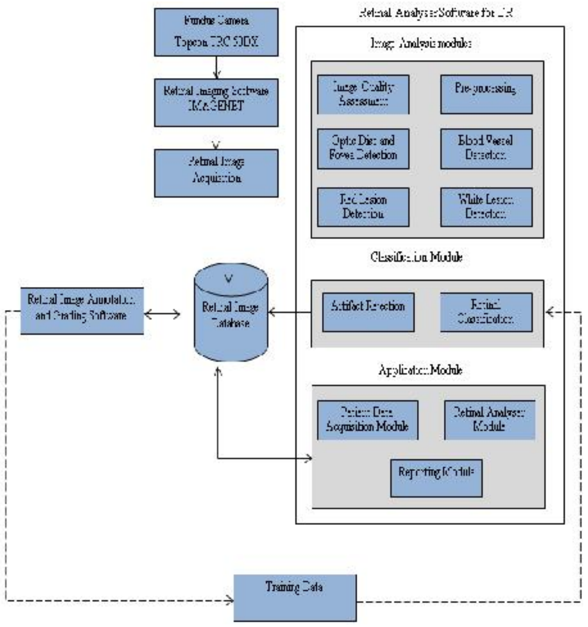


Figure 1: System Architecture

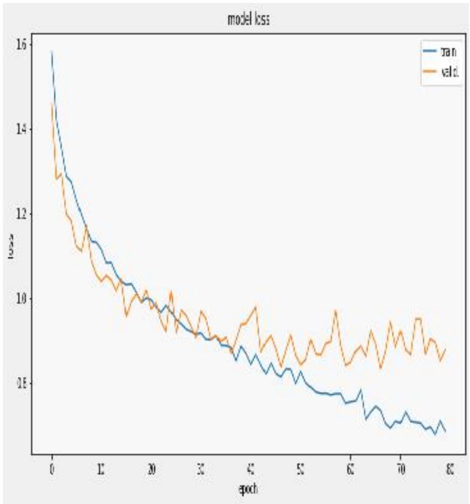
V. ALGORITHM USED

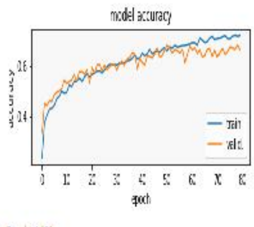
Dataset values converted into array values which is going to give to the algorithm to find accuracy. Select the algorithm based on the accuracy and analyses the data by using the algorithm. Convolutional neural networks (CNNs) are widely used in pattern- and image- recognition problems as they have a number of advantages compared to other techniques.

VI. RESULT

We have chosen Convolutional Neural Network because they have achieved higher accuracy in Image Net competition. The validation loss fluctuates in the first epoch, and it becomes stable at the end of training. The training and the validation loss is decreasing continuously, which shows that training for a larger number of epochs can help us achieve better results .

	precision	recall	f1-score	support
No DR	0.95	0.96	0.95	810
Mild	0.75	0.66	0.70	810
Moderate	0.69	0.89	0.78	810
Severe	0.69	0.66	0.68	810
Proliferate DR	0.76	0.65	0.70	810
accuracy			0.76	4050
macro avg	0.77	0.76	0.76	4050
weighted avg	0.77	0.76	0.76	4050





VII. CONCLUSION

Our study has shown that the five-class problem for national screening of DR can be approached using a CNN method. Our network has shown promising signs of being able to learn the features required to classify the fundus images, accurately classifying the majority of proliferative cases and cases with no DR. As in other studies using large datasets high specificity has come with a trade off of lower sensitivity8. Our method produces comparable results to these previous methods without any feature-specific detection and using a much more general dataset. The potential benefit of using our trained CNN is that it can classify thousands of images every minute allowing it to be used in real-time whenever a new image is acquired. In practice images are sent to clinicians for grading and not accurately graded when the patient is in for screening. The trained CNN makes a quick diagnosis and instant response to a patient possible. The network also achieved these results with only one image per eye. The network has no issue learning to detect an image of a healthy eye. This is likely due to the large number of healthy eyes within the dataset. In training the learning required to classify the images at the extreme ends of the scale was significantly less. This could have severely hindered our results as the images are misclassified for both training and validation. In future, we have plans to collect a much cleaner dataset from real UK screening settings

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