



Diabetic Retinopathy Detection

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Abstract: Diabetic Retinopathy (DR) affects 1 in 3 peoples with diabetes and remains the leading cause of blindness in working-aged adults. Currently, detecting DR is a manual processing and time consuming that needs a trained clinician and evaluate digital color fundus photographs of the retina of eye. By the time readers can submit their reviews, often a day or two later, the delayed results lead to lost follow up, miscommunication, and delayed treatment. The need for a comprehensive and automated technique of DR screening has long been accepted, and previous efforts have made good progress using image classification, pattern recognition, and machine learning. This system uses ensemble learning technique to detect diabetic retinopathy from scan images. Inception V-4, Xception, ResNeXt are the three base models used which are modified and optimized to avoid overfitting, underfitting issues. The base models are individually optimized and their predictions from final layers are combined using algebraic combiner (maximum rule). Each base model differ in performance when using different datasets, therefore final output does not always depend on one higher performing base model.

Keywords: Xception, Inception V-4, ResNeXt, Ensemble Learning

I. INTRODUCTION

Diabetic retinopathy is an eye disease mainly caused due to diabetes which effect up to 80 percent of all patients who have had diabetes for 10 years or more. It is main causes for blindness in working population. At least 90 percent of new cases can be reduced if there were proper treatment and monitoring of eyes. Detecting the DR symptoms in time can prevent the vision impairment in majority of cases. But it is difficult with present tools and methods. There is need for automated DR detection tools and methods. To detect the DR the highly trained medical professionals are need to study the fundus of eye. Deep learning method has been used for detection of DR with high performance. Here there is need for more accuracy than the present methods and tools that used for detecting DR. So we proposed a new model that uses ensemble approach to give a better result in any fundus images. This technique uses three algorithms Inception-v4, Xception and ResNeXt that works separately and produce a final result by applying maximum rule which gives the better result among three.

II. THEORY

A. Xception

The Xception design, introduced by Francois Chollet, is an extension of the origination design. This architecture could be a linear stack of depthwise divisible convolution layers with residual connections. The depthwise divisible convolution aims to scale back machine price and memory needs. Xception has thirty six convolutional layers structured into fourteen modules, all embrace linear residual connections, apart from the primary and last modules. The divisible convolution in Xception separates the educational of channel-wise and space-wise options. Also, the residual affiliation introduced by Heet al. helps to unravel the problems of vanishing gradients and depictive bottlenecks by making a crosscut within the successive network. This crosscut affiliation is creating the output of an earlier layer offered as input to the later layer employing a summation operation instead of being concatenated.

B. Inception V-4

Inception V4 was present in combination with Inception-ResNet by thee researchers a Google in 2016. The main aim of the paper was to decrease the complication of Inception V3 model which give the state-of-the-art accuracy on ILSVRC 2015 challenge. The initial set of layers which the paper refers "stem of the architecture" was modified to make it more uniform. These layers are used before Inception block in the architecture. This model can be trained without separation



of replicas unlike the old versions of inception which required different replica in order to fit in memory. This architecture use memory optimization on back propagation to decrease the memory requirement.

C. ResNeXt

ResNeXt could be a easy and standard network architecture. it's used for image classification. This network is created by continuation a building block that cluster a group of alternation with constant topology. This style leads to a homogeneous and multi-branch design. This design has solely a couple of hyper-parameters to line. This strategy exposes a replacement dimension that is named "cardinality" (the size of the set of transformations), as a necessary consider addition to the size of depth and dimension. The experiments reveal that increasing cardinality is high effective at benefiting model performance than increasing the dimension or depth of the network. The experiments conjointly propose that residual connections are used for improvement, wherever aggregative alternation are stronger representations.

D. Ensemble Learning

Ensemble learning is the process by which different models, such as classifiers or experts, are strategically generated and merge to solve a particular computational intelligence problem. Ensemble learning is primarily used to enhance the performance of a model, or decrease the likelihood of an unfortunate selection of a poor one. Other applications of ensemble learning include assigning a confidence to the decision made by the model, selecting optimal (or near optimal) features, data fusion, incremental learning, nonstationary learning and error-correcting. This article focuses on classification associated applications of ensemble learning, however, all principle ideas described below can be easily generalized to function approximation or prediction type problems as well.

III. RELATED WORK

In this paper ^[1] using transfer learning technique a convolutional neural network model with Siameselike architecture is trained. This model takes binocular fundus images as inputs and learn their correlation to help make a prediction. Instead of adopting fundus images of single eye as input like most works did, the model has a novel Siamese-like CNN model with weight-sharing layers based on Inception V3, which is able to accept fundus images of both eyes as inputs and outputs the classification result of each eye at the same time. To be better modified to the model, those binocular fundus images have been coupled and pre-processed correspondingly before fed into the network. Besides, the model with uncoupled inputs is evaluated and it confirms the effectiveness of the proposed binocular design. Comparing with latest algorithm this technique has lower accuracy and increased training time.

In this paper ^[2] a generalization of back propagation method is used in order to train convNets that produce high-quality heat maps. The sparsity of the heatmaps are enhanced while training them to improve the quality of the heatmaps. One of the best part is detection performance is not affected much by quality of images, which means very good detections are produced in blurry images. Because this system relies on pixel-level information for training, higher performance in smaller dataset were able to achieve. Theoretically, increasing the sparsity of the heat map should also speed up the training speed. But here it didn't, which is a disadvantage of this network. Transfer learning from an already trained deep convolutional network can be used to train with small training data for deep learning and decrease the cost of training from scratch.

In this work ^[3] a pre-trained Inception-V3 model is employed to require advantage of its Inception modules for diabetic retinopathy detection. Here, transfer learning on a deep CNN model that was pre-trained on a set of the ImageNet's dataset is enforced. A pre-trained Inception-V3 model downloaded and a classifier aspect to classify structure image into healthy and unhealthy classes. A pre-trained Inception-V3 model downloaded and a classier aspect to classify structure footage into healthy and unhealthy classes. Keras library is employed to import the pre-trained model. When building the model, a every elite subsample of the EyePacs DR Dataset which is hosted on Kaggle platform is employed for model coaching and testing. This model has superior performance over different models mistreatment a similar formula that is SGD with ascending learning rate. This system needs pre-trained model that isn't obtainable for all things.

This paper ^[4] explores the employment of assorted convolutional neural network Architectures on pictures from the dataset when being subjected to acceptable image process techniques like native average color subtraction to assist in lightness the relevant characteristics from a funduscopy. EyePACS dataset is used to train the moddel used. VGG19, VGG16, Inception V-3 are the three models used in this paper. The main difference between VGG16 and VGG19 in terms of network architecture is the additional convolutional layer in the 3rd, 4th and 5th convolutional blocks. Among these networks inception model has more efficient computation and performance due to increased number of layers. In results, inception outperformed VGGNets. Incresed number of layers in inception networks caused increased training



time. The use of ensemble models or ensemble classifiers has proved to provide better result than a single complex algorithm in many problems as ensembles are able to better resolve the bias variance trade-off.

In this work^[5] several ensemble structures used for retinal vessel segmentation. An hymenopterous insect colony optimization algorithmic program is employed to optimize the ensemble structures supported many criteria as well as the range and therefore the ensemble member's performances. The results make sure the effectiveness of the ensemble learning and therefore the advantage of ensemble optimization. Here 5 non-optimized ensemble models area unit made. Ensemble A is made supported GMM strategies trained and tested on DRIVE victimization totally different range of Gaussian models ($k=1, 5, 10, 15, 20$). As all of these methods are similar except in one parameter, the diversity is not expected to be high. Ensemble B is also constructed using GMM methods however, STARE dataset is used to train some of the classifiers which are then tested on DRIVE. Thus, the diversity of ensemble B is higher than that of ensemble A, as different training sets are used. Ensemble C was constructed by using different LDC-PCA methods with different number of features. Ensemble D was formed by all GMM and LDC-PCA methods. MSLTA, the accommodative thresholding approach, kNN classifier and every one of the GMM and LDC-PCA ways were combined along to make ensemble E. Overall performance the ensemble is sweet attributable to victimization economical base model.

The MLPNN^[6] is used for detect diabetic retinopathy in retinal images as normal and abnormal. Train N times method is used to train MLPNN to find the best feature subset. The MLP NN is designed using one hidden layer with single neuron. The numbers of neurons are increased. Same process is repeated with two hidden layers. Various parameters are changed progressively to set optimal neural network with best results and least complexity. It is observed that with single hidden layer gives better performance. The number of Processing Elements (PEs) in the hidden layer also diverse. The network is trained and final minimum Mean Square Error (MSE) is obtained on cross validation data when 11 PEs are used in the hidden layer. Best results are obtained when 10% exemplars are used for cross validation (CV) and 90% for training neural network. For training and Cross validation of data set, the system obtained relatively high accuracy of 100%.

This system^[7] investigated the automatic detection of DR using deep neural networks, also provide appropriate suggestions to DR patients. For this method a new novel dataset of DR funds image is proposed, that is moderate in size and labeled by the proper treatment method that is required. Using this dataset, deep convolutional neural network has trained to grade severity of DR funds images. This system achieves an accuracy of 88.72%.

In this system^[8] procedure of diabetic retinopathy detection is automated using feed forward neural network which gives results of many patients within a short time. It is fully automated approach and implemented using open source tools. This method is economical in terms of hardware and other resource requirements. The system gives 75% of accuracy.

In this paper^[9] provides classification of DR fundus images according To severity of disease using convolutional neural network.. In proposed modified Alexnet architecture, the testing and training is done using me as is or dataset. This architecture is used to categorize DR funds images with application of pooling, softmax and ReLu layers. This architecture gives 96.6% of accuracy.

This paper^[10] presents a new feature extraction method using modified Xception architecture for the detection of DR. This method is based on deep-water association that merges multilevel features form separate convolutional layers of Creation architecture. These extracted features are fed into MLP to be trained for DR severity classification. The accuracy of this method is 83.09%.

The aim of this paper^[11] Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs The assessment of retinal fundus photographs of diabetes affected adults revealed the significance of having an algorithm for detecting the diabetic retinopathy. This has developed completely based on machine learning and it possess high levels of sensitivity and specificity in the detection process. Deep research in this area will help to extend this facility into the clinical setting and also this can improve the status of the current ophthalmologic assessment. Diabetic retinopathy involves different steps. The neural network generates continuous no from 0 to 1 for referable diabetic retinopathy. There are two operating points are being selected for the algorithm from the development set and also the operating curves are being plotted. The first operating point detects the specificity of the ophthalmologists in the derivation set for detecting the referable diabetic retinopathy. The next operating point refers to the sensitivity for detecting the diabetic retinopathy. The sensitivity and specificity of the algorithm for detecting referable diabetic retinopathy(RDR), defined as moderate and worse diabetic retinopathy, referable diabetic macular edema, or both, were generated based on the reference standard of the large decision of the ophthalmologist panel.

In this paper^[12] pre-processing and feature extraction are also done for the detection of diabetic retinopathy. The images are divided into two different datasets. First one is a normal stimulus and the other is diabetic affected retinal images. The total 14 biologically significant characteristics are extracted from normal and diabetic retinal fundus image data sets. From this extracted features, most significant seven features are used for comparison. From the results, it is observed that exudate area is the best feature out of all which is primarily used for diabetic detection. The features used in this study are specific because of their biological relevance and previously reported results. In future, more options



are often extracted from attributes. The assessment of clinical report revealed that more than ten percentage patients with diabetes carries the risk of Diabetic Retinopathy (DR). This is an eye ailment which affects eighty to eighty-five percentage of the patients with diabetes for more than ten years. In clinics, this disease is detected and analyzed by observing the retinal fundus images. It's difficult to process the raw retinal fundus images through machine learning algorithms. In this paper, the extraction of green channel, histogram, equalization, image enhancement and resizing techniques are used to the pre-processing of raw retinal fundus images. The experiments are execute using Kaggle dataset and the results are evaluated by considering the mean value and standard deviation for extracted features. The result yielded exudate area. The result shows the tota absence in normal diabetic images and its presence in the three classes of diabetic retinopathy images called mild, normal and severe.

In this paper ^[13] the retinal images are evaluated to diagnose the DR. It takes a huge amount of time and at the same time resource demanding to manually grade the images so that the severity of DR can be defined. This problem can be noticed only when the tiny blood vessels within the retina are destroyed. Blood flows from this blood vessel and the features are formed from the fluid in the retina. The process of diabetes retinopathy detection consist of major three phases. That are pre-processing, feature extraction and classification. Here, the NN classification approach is proposed for the diabetes retinopathy detection. The proposed model is compared with SVM classification model. It is analyzed that results are optimized up to 5 percent with the use of NN. The proposed model is implemented in MATLAB and by using certain parameters the results are analyzed. The medical images include several kinds of measurements. In which some are the RF signal amplitude in MRI, the acoustic pressure found in ultra sound images or the radio absorption in X-ray imaging. If a single measurement is performed at each location in the image, it is known as scalar. It is essential to design a software to control the high level of imaging. New algorithms are designed by signal and image processing technology based on the partial differential equations and curvature driven flows.

Diabetic retinopathy (DR) ^[14] is a common retinal complication related to diabetes which causes blindness in both the middle and advanced age group people. The analysis of the US National diabetes information data shows that 23.6 million people of the US population have diabetes and in this only 17.9 million cases are diagnosed. This replicates the need of early detection of the disease and the remedial should be taken to avoid the vision loss. An automated DR diagnostic system is highly essential to execute the tests repeatedly. Ophthalmologists usually use the color fundus images to study the eye related problems. The severity of diabetic retinopathy is determined by using the spatial distribution of mycroaneurysms and hemorrhages in relation to the fovea. In this paper, the efficient methods for the early detection of diabetic retinopathy is been developed. In this system, apart from the most methods of learning techniques, geometrical relationships of different features and lesions are used along with simple morphological operations to obtain a very robust system for the analysis of retinal images.

In this paper ^[15] a new method of blood vessel extraction which is an improvement over the earlier developed matched filter is been proposed. It is a new method of hemorrhages detection. Also classify the retinal cases using an new nonparametric technique with higher classification accuracy. The objectives of this work are, (i) the detection of blood vessels, (ii) detection of hemorrhages, and (iii) classification of the detections into normal, moderate non-proliferative diabetic retinopathy (NPDR) and severe NPDR. The different stages of diabetic retinopathy are classified based on the detection and quantification of blood vessels and hemorrhages present in the retinal image. The density analysis and bounding box techniques are used to detect the hemorrhages. The division of different levels od eye disease was done with the use of Random Forests Technique based on the area and hemorrhages. Accuracy assessment of the classified output disclosed that normal cases were classified with 90% accuracy while moderate and severe NPDR cases were 87.5% accurate. The lack of proper functioning of pancreas in secreting enough insulin is the major reason behind the disease Diabetes. This in progress affects the circulatory system which includes the retina. It also occurs as a result of long term accumulated damage to the blood vessels. This may decline the eye vision and leads to the diabetic retinopathy. After 15 years of diabetes about 10% of people become blind and approximately 2% develop severe visual impairment.

The aim of the paper ^[16] is to investigate the small scale feature propagation to improve the classification of diabetic retinopathy. Here there is three different residual architectures. And their residual and skip connection is tested. Residual connection improves the detecting small scale features. Here skip connection is detriment to overall performance.

This paper ^[17] develops an algorithm for detecting the diabetic retinopathy and to improve accuracy of the existing system. This algorithm was trained and tests using fundus and mages. All input images are categorized in to four stages of diabetic retinopathy. These images are captured under illumination conditions.

This paper ^[18] is to develop an automated model identify the antecedents of diabetic retinopathy. This developed model is trained with back propagation neural network, deep neural network, and convolutional neural network. After testing this model with CPU trained neural network it gives only low accuracy. For get better accuracy select the proper features from the input image. Here to identify the class weighted fuzzy c means algorithm is used. This model helps to identify the proper class of DR.



This paper ^[19] aims to implement and design the GPU accelerated deep convolutional network to diagnose automatically. This classifies the images of retina in to five stages of disease. This involves three convolutional neural network and designing their architecture and find their quadratic kappa scores.

The aim of the paper ^[20] is to develop an automated fundus image analysis system to detect the stages of diabetic retinopathy early to modify telephthalmology. This system captures retinal fundus images of diabetic patients by fundus camera at screening camp site. By using preprocessing techniques the captured images are accurately classified as normal or with DR. From the camp site the images that effected with DR sent to ophthalmologist.

IV. CONCLUSION

From all these papers, it is clearly visible that machine learning models has improved performance over the years to detect diabetic retinopathy with better accuracy. Existing algorithms have evolved to improve their prediction accuracy. By using this prediction technique we can reduce human intervention and DR diagnosis time. Even though prediction is not hundred percentage accurate, the results are reliable. But with proper data training and modification these techniques are very useful.

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