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Diabetic Retinopathy Detection Using Convolution Neural Networks

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Abstract: An image is defined as a scalar in case of performing a single measurement at every location of the image. As the invasive devices, having higher speed, and more accuracy are developed rapidly, a great innovation can be seen in the progress of medical imaging in last few decades. There is a necessity of precise software for handling these kinds of images of higher quality. The previous technique aims to pre-process the image for detecting the diabetes retinopathy (DR) and deploys the textural feature analysis to extract the pre-processed image. The diabetic portion is segmented using an optical disk segmentation (ODS) method. This research work expands the previous technique with the implementation of Convolutional Neural Network (CNN) algorithm. Google Colab is executed to simulate the suggested technique. Various parameters are utilized to analyze the results.

Keywords: *Diabetic retinopathy, Deep Learning, CNN, SVM, Back Propagation*

1. Introduction

In order to produce an image, the measurements of 2D (two-dimensional) and 3D spaces are collected that is called pixels. The clinical images contain several kinds of pixels due to their generation from diverse sources such as X-ray images, MRI scans or ultrasounds [1]. An image is called a scalar in case the measurement is found in the form of one same category for every location in images. The clinical imaging is emerging as an effective technology due to its efficacy to offer invasive devices at higher speed, and accuracy in diverse applications. The images of greater quality are handled using a precise software. Thus, PDEs (partial differential equations) and CDFs (curvature driven flows) are considered to formulate novel algorithms for signal and image processing technologies [2]. The mathematical models help to design the biomedical computing. The novel algorithms, which utilize data extracted from images, are considered to build a standard technique. This technique facilitates a scientific growth of numerous domains.

Diabetic retinopathy (DR) is an ailment which may lay impact on retina of a human eye. This disease may infect the entire eye and a permanent blindness is occurred in case of improper treatment [3]. The professional eye specialists and precise knowledge related to such disease is not available properly in the emergent countries. Though, some automated tools are presented and this disease must be treated at initial phase to prevent the patients from this disease. Various solutions are there for preventing this disease. The essential task is to diagnose DR and monitor the diabetic patients continuously [4]. Diabetic retinopathy is diagnosed by computing the retinal images. For defining the severity of DR, to grade the images in manual way consume enormous volume of time and resources.

This issue is occurred due to the damage in tiny blood vessels which are present in the retina. The blood is flown from the tiny blood vessel and the fluid present in retina is considered to extract the attributes [5]. These attributes play a significant role to examine this issue as the fluid and blood is flowing from the blood vessels. DR is classified into 3 categories: normal, PDR (proliferative diabetic retinopathy) and NPDR (non-proliferative diabetic retinopathy), on the basis of their severity. NP is a premature phase of DR whose classification is done according to the availability of MAs (micro aneurysms). In retina, the entry of oxygen leads to produce the novel blood vessels due to which the vision becomes blur as the disease is transmitted [6]. Consequently, there is need to screen the retina of diabetic patients on regular basis. The automated or BA (computer-based analysis) is useful to attain a clear vision of the retina of diabetic patients [7].

The fundus images are exploited to evaluate DR and recognize its attributes. Even though, the particular attributes of retina are analyzed, researchers are incapable of developing a consistent or vigorous method. The severity of DR is diagnosed and graded in automatic way using a three-fold algorithm. Thereafter, the fundus images of eyes are taken into consideration. The first phase is executed to pre-process the images with the objective of rectifying some issues regarding non-clarity, image blurring or image size [8]. Moreover, this process of resizing an image is employed. It aims to restore the image and convert the color space. The last phase emphasizes on enhancing the image. The task of converting color space is deployed for transforming the color fundus image into HIS (hue, intensity, saturation) format. This format is implemented to decouple the color model space from color images. In the first stage, HE (histogram equalization) is carried out. Afterward, the contrast is enhanced and the scaling of the pixel intensities is done [9].

The procedure of extracting the candidate makes the deployment of various morphological operations to recognize MAs (micro-aneurysms) and exudates attributes. Moreover, the image is reversed using the invert image technique [10]. The next stage is executed to fill the holes. The exudates and MAs are recognized from the color image to extract the attributes from fundus images. This process utilizes different classification techniques that employs the outputs of computed attributes as input. SVM

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(Support Vector Machine) is a major binary classifier [11]. This technique concentrates on analyzing the issue of recognizing multi-class pattern. Two schemes are adopted for dealing with this issue. Euclidean distance from a testing to the particular training sample is utilized to compute the value of KNN (K-Nearest Neighbor) algorithm. NB (Naïve Bayes) algorithm is planned depending upon the notion of Bayes' theorem [12]. This algorithm is based on the hypothesis that there is not any association among predictors. This hypothesis defines that the incidence of a specific attribute available in a class is not related to the accessibility of another feature.

2. Literature Review

Ashish Issac, et.al (2018) offered a novel algorithm to computerize the pathologies detection. These were the diagnostic characteristics of diabetic retinopathy [13]. The main goal of this research was to strategically employ these characteristics in a system for categorizing the severity of this disease's danger. For the purpose of emphasizing the brilliant lesions in this work, a normalizing approach was used. The use of anisotropic diffusion and an intensity threshold allowed for the detection of these lesions. A shade-approved green channel image was used to accurately detect red lesions. Geometrical features reduced the complexity of the detection system and improved its effectiveness by removing FPs (false positives). A unique vocabulary learning-based technique for automatically detecting diabetic retinopathy was developed by Narjes Karami et al. (2017) [14]. Digital fundus images were used in this study to look for diseases. The created method was based on the K-SVD approach's optimal atomic demonstration of fundus images according to learned dictionaries. On the other hand, to distinguish between the regular and diabetic categories, the K-SVD learned dictionaries needed to be strong. It suggested that the test image belonged to the class with the fewest possible ideal definite atoms. Thirty colour fundus photos were used in this study to test how well the developed approach worked. For normal photos, this method had a 70% accuracy rate, and for images of diabetes, it had a 90% accuracy rate. By carefully locating and counting the number of micro aneurysms in colour fundus pictures, Shailesh Kumar et al. (2018) illustrated a new technique for DR identification [15]. Early detection of micro aneurysms was crucial. The process of DR detection began with this. As time went on, more methods for identifying and diagnosing DR were suggested. Initially, many pre-processing techniques were used. PCA, CLAHE, morphological analysis, and common filters for detection were all used in this study. The diabetic retinopathy condition was identified by the linear SVM classifier. The suggested method had a 96% sensitivity and 92% specificity for DR diagnosis.

Enrique V. Carrera, et.al (2017) offered a computerized diagnosis of the DR illness. Here, helping doctors identify DR illness early was the main goal [16]. Images of the retina were subjected to digital processing for this investigation. The automatic classification of non-proliferative DR at a retinal picture was the main focus of this work. The separation of blood vessels, MA, and hard exudates for feature extraction was part of the first stage of image processing. These characteristics could be used by an SVM classifier to determine the degree of retinopathy in all retinal images. The studied approaches' successful sensitivity and prediction efficiency were 95% and 94%, respectively, according to the test results. This method's effectiveness was assessed in terms of how well it handled fluctuations in several measures.

In a database of retinal image data, Nikita Kashyap, et al. (2017) provided a method for locating and extracting the necessary image [17]. To create an extraction approach, the colour histogram feature was extracted. After that, by entering the number of bins in the histogram, the feature vector with the requisite magnitude had been found. To verify the similarity between the query and database image, the Euclidean distance between them was calculated. In HSV colour space compared to RGB colour space, the colour histogram extraction framework performed better. By focusing on the diabetic image, the suggested framework spared professionals the time-consuming task of assessing all fundus photos. To increase the effectiveness of DR diagnosis, a perfect DR image management system was designed in this study. Using a novel technique, Harini R. et al. (2016) proposed to diagnose diabetic retinopathy. Morphological image processing and fuzzy C-Means (FCM) clustering for detection were integrated in the suggested approach. The pre-processing of images involved a number of stages [18]. The suggested method used morphological techniques to conduct blood vessel segmentation. For this endeavor, retinal pictures were acquired from hospitals and other freely accessible databases. SVM classifier was used in this study to distinguish between normal and diabetic retinal pictures. The accuracy, sensitivity, and specificity of this classifier were 96.67%, 100%, and 95.83%, respectively.

3. Research Methodology

The outcomes of extensive research into the techniques for a binary categorization of DR are positive. To prediction the Diabetic type model of transfer learning is applied which is the combination of VGG16 and CNN model. The VGG16 is used as the base model over which CNN model is used for the training.

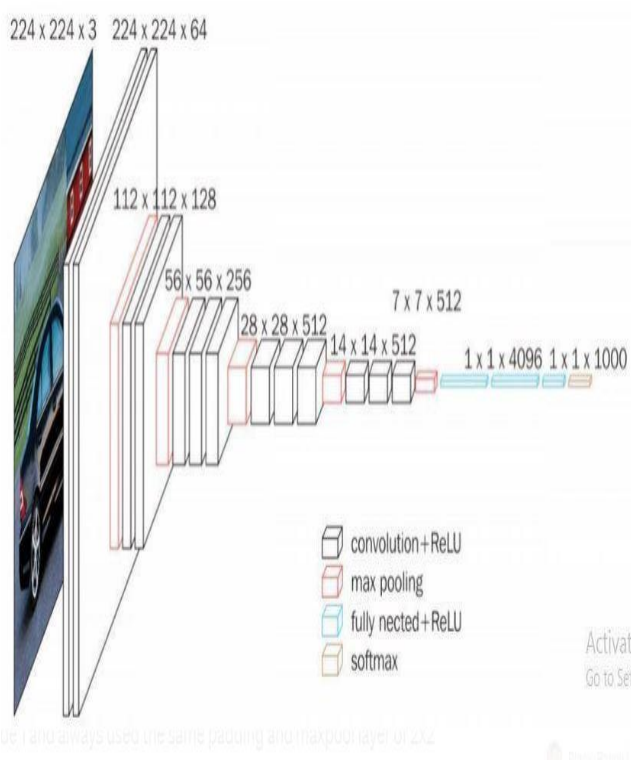

Fig. 1. VGG16 Model Architecture

Following are the various specifications of VGG16 Model: -

1. The 16 in VGG16 refers to 16 layers that have weights. In VGG16 there are thirteen convolutional layers, five Max Pooling layers, and three Dense layers which sum up to 21 layers but it has only sixteen weight layers i.e., learnable parameters layer.

2. VGG16 takes input tensor size as 224, 244 with 3 RGB channel
3. Most unique thing about VGG16 is that instead of having a large number of hyper-parameters they focused on having convolution layers of 3x3 filter with stride 1 and always used the same padding and maxpool layer of 2x2 filter of stride 2.
4. The convolution and max pool layers are consistently arranged throughout the whole architecture
5. Conv-1 Layer has 64 number of filters, Conv-2 has 128 filters, Conv-3 has 256 filters, Conv 4 and Conv 5 has 512 filters.
6. Three Fully-Connected (FC) layers follow a stack of convolutional layers: the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer.

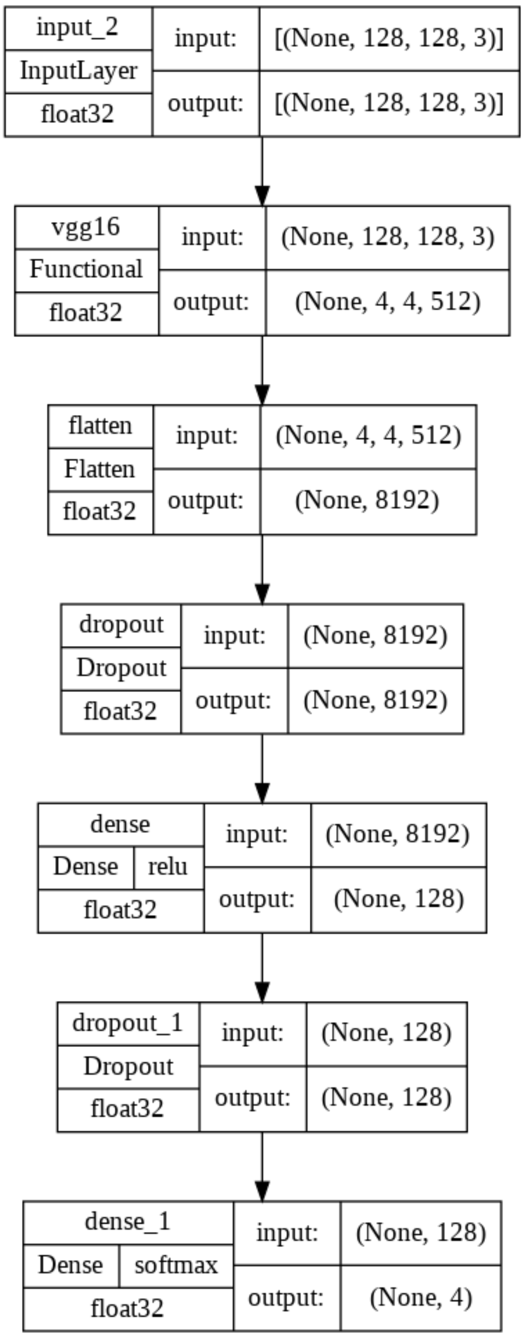

Fig. 2. Proposed Transfer Learning Model

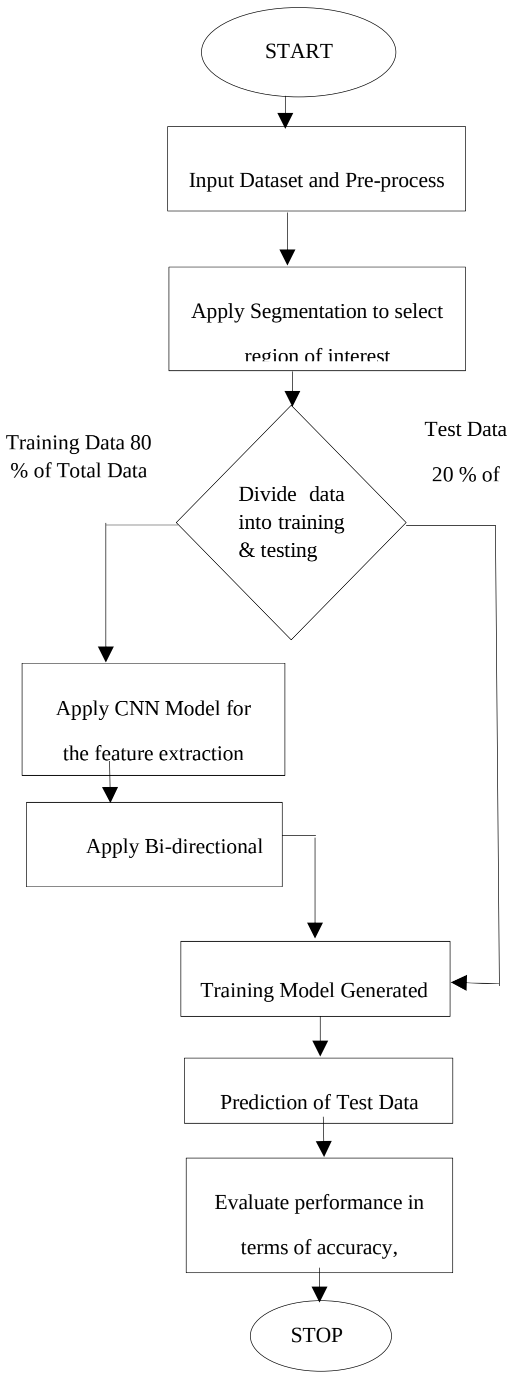

Fig. 3. Proposed Model

4. Results & Discussion

4.1. Dataset, Hardware and Software

The system is tested on a dataset extracted from the Kaggle, and around 80,000 images (having 6M pixels and scales of retinopathy, per image) are included in it. These images are resized and CNN (Convolutional Neural Network) is executed on high-end GPU namely NVIDIA K40c for training the entire dataset. 2880 CUDA cores and cuDNN (CUDA Deep Neural Network library), utilized to learn GPU, are supported in this package.

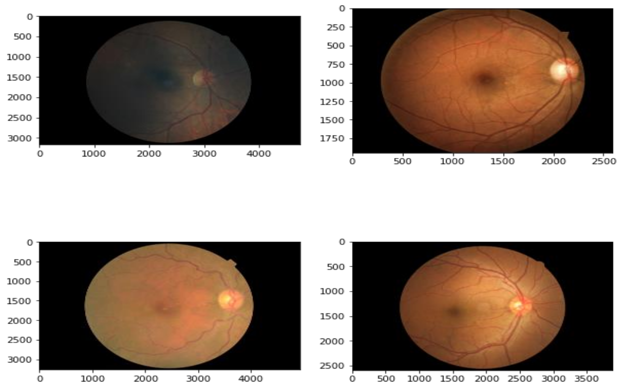

Fig. 4. Data Sample images

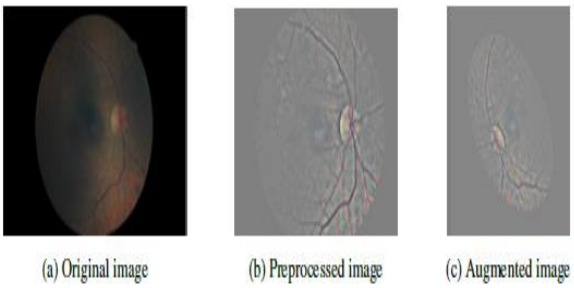

Fig. 5. Illustration of the pre-processing and augmentation operations

4.2. Preprocessing

The images taken from patients having varying ethnicity, age groups and extremely varied levels of lighting in the fundus photography are comprised in the dataset. It may lay impact on pixel intensity values in the images and assists in generating redundant variation which has no association with the classification levels. For tackling this issue, OpenCV is utilized to normalize the color on the images. Figure 2 (b) demonstrates the pre-processed image. The resolution and memory size of these images is found higher. the resizing of this dataset is done to 512x512 pixels for retaining the complex attributes which will be recognized. Another task is to alleviate the dataset according to a memory size which is manageable for NVIDIA K40c.

4.3. Training

Around 10,290 images are employed to pre-train CNN (Convolutional Neural Network) at first with the objective of acquiring quick results of classifying the data. No time is wasted for substantial training. Thereafter, 78,000 images are utilized to train the network for further 20 epochs. In a dataset, the major issue before NNs is severe over-fitting. The utilized dataset classifies the majority of the images in one class which represents no symptom of retinopathy. This issue is tackle using class weights in real time in the network. after loading each batch for BP (back-propagation), a ratio Harry Pratt/Procedia Computer Science 00 (2016) 000–000 5 respective with the total images whose classification is done in the training batch and showing no symptoms of DR, is considered for updating the class-weights. It results in lessening the risk of over-fitting to a certain class which must have to mitigate greatly. SGD (Stochastic Gradient Descent) is employed with Nestrov momentum to train the network. the lower learning rate is considered 0.0001 for 5 epochs for stabilizing the weights. It is extended to 0.0003 for the substantial 120 epochs to train on the preliminary 10,290 images. The accuracy is found 60% and time consumed to train the network is measured 350 hours. Later, the full training set of images at lower learning rate is employed to train the network. This network yields an accuracy of 95% for couple of huge epochs.

4.4. Augmentation

The network is trained on the original pre-processed images. After that, the data is augmented in real-time for enhancing the localization potential of the network. The random rotation within 0-90 degrees, random yes or no, horizontal and vertical flips, and random shifts horizontally and vertically, are utilized to augment every image at random during each epoch. The outcomes of augmenting an image are also demonstrated in fig 5(c).

4.5. Result Comparison

The system is validated on 5,000 images after saving them from dataset. The validation images are performed on the network in 188 seconds. For 5-class problem, the specificity metric is utilized to define the number of patients whose recognition is done as patients without DR out of the total normal patients, and sensitivity metric is utilized to illustrate the number of patients which are diagnosed with DR from the total number of Diabetic Retinopathy cases. The accuracy describes the number of patients who are classified correctly. It is analyzed that the utilized network offered an accuracy of 94%, specificity of 95% and sensitivity of 94%. This network classifies Diabetic Retinopathy in 5 categories which are defined in numerical way in which 0 represents that no DR is there, 1 for mild DR, 2 for Moderate DR, 3 for severe DR and 4 for Proliferative DR.

Table 1. Result Comparison

Models	*Accuracy*	*Sensitivity*	*Specificity*
Back Propagation [19]	88 Percent	88.4 Percent	83.5 Percent
Neural Networks [20]	93 Percent	90 Percent	91 Percent
SVM [21]	82 Percent	82 Percent	88 Percent
Proposed Model	94 Percent	95 Percent	94 Percent

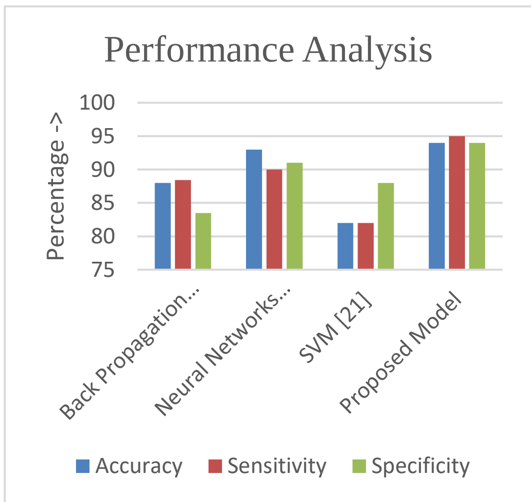

Fig 6. Model Comparison

As shown in figure 6, the performance of proposed model is compared with other models for the diabetic retinopathy detection. The proposed model is compared with back propagation model, Neural Network and SVM Models which give 88 Percent,93 Percent, 82 Percent accuracy respectively. The proposed Model has maximum accuracy of 94 percent which prove reliability of the proposed Model.

5. Conclusion

The retina of the eye is harmed by the problems of Diabetes Mellitus. This condition is regarded as the leading cause of eyesight loss in the United States of America. Indistinct vision, difficulty distinguishing colours, floaters, and even absolute blindness are some symptoms of this illness. To avoid diabetic retinopathy, it is crucial for diabetics to have their vision checked at least once a year. The detection of DR illness typically involves three phases. Pre-processing, feature extraction, and classification are the processes involved. For the purpose of categorizing diabetic areas from retinal pictures, this work implements the CNN classifier. In terms of many performance indicators for DR detection, the new approach performs better than the older approach. The proposed shows approx. 3 Percent improvement in the results as compared to other models.

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