DIAGNOSIS OF DIABETIC RETINOPATHY USING CONVOLUTION NEURAL NETWORKS

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Abstract— *Diabetic Retinopathy is a complication of diabetes, especially for those with type 2 diabetes. High blood sugar levels over a period of time can damage the blood vessels in the retina, making them, swell and leak. In some cases it may also happen that they block blood from passing through. These lead to development of irregular fresh blood vessels in the retina. All of these conditions affect the vision adversely leading ultimately to loss of vision. The early stages of diabetic retinopathy are painless and symptom less, and hence can go undetected for a long time. It is therefore recommended for diabetics to have an annual eye fundus examination. As the disease advances certain symptoms may occur like: Sudden changes in vision, Reduction in night vision, Distorted vision, Impaired colour vision, Eye pain.Identification of Diabetic retinopathy at early stage is useful for for clinical treatment. Researchers already proposed several feature extraction techniques to classify the retinal images with and without diabetic retinopathy but still classification technique is still complex task for retinal image. Deep learning is widely used in numerous applications one of them being medical analysis. Feature extraction and Image classification are considered to be the most popularly used approaches done using deep learning process. In this proposed work, we used deep learning technique namely convolutional Neural Network (CNN) an efficient model for detecting Diabetic Retinopathy by preprocessing digital fundus images and further segmenting it for feature extraction. The feature extraction of the images is done by training the convolution neural networks to classify whether the image is affected or not affected by Diabetic retinopathy. The effectiveness of the proposed model is assessed which produces 81.27% affectability, 99.91% explicitness, and 99.71% precision. The fulfillment of the model is progressively precise when contrast with existing as it makes use of CNNs to train and validate the data set.*

Keywords *— Diabetic Retinopathy, Classification, Deep Learning, CNN Extraction, Medical Image Analysis.*

I. INTRODUCTION

An AI Neural network is a machine learning model which tried to imitate the way the brain learns. This is usually done by initially providing a set of data to the AI algorithm for learning. The data sets are tagged data. The AI reads these data and identifies a pattern of recognition. It then uses this pattern to identify similar data sets [1]. It comprises of various "neurons" that are connected in specific ways and give output based on a weighted function of inputs. There are many ways it can be done, but for starters, you can think of neural network as consisting of layers of neurons, where each neuron in a layer outputs a weighted aggregate of the neurons of the past layer. The best part of neural networks is that they can be "trained" similarly to humans - it starts random, and gets better as you show it samples and tell it if it's done well. One of the most vital parts of the deep learning approach is the extraction of features from the dataset that is being given and trained[2][3]. Training

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a neural network depends on having a good sampling basis. Deep learning is when computers look at huge proportions of samples to distinguish why they are classified as they are to find what is in common with them, and then use this quantitatively constructed data to try to predict answers of other samples in the same field without human input or supervision. Deep Learning can play a major role in analyzing medical images quickly (a lot faster than human, see Conner's answer below for an example) and provide insights to the clinician to better understand a complex clinical scenario. For example, currently radiologists need an ample amount of time to provide a report based on a radiology image (e.g. X-ray, MRI, CT, ultrasound). This increases the clinician's decision making time significantly, which is unwanted when there is a critical clinical condition and a quick and timely decision is a must in order to administer a treatment plan to save a patient[4].

Deep learning can alleviate this problem by automatically learning important features from the plenty of medical images available in the medical domain; then, suggesting the radiologist options to consider during report generation to speed up the clinical work flow. More or less all medical imaging modalities can be benefited from this[5].

Many researchers have already shown the effectiveness/applicability of various deep learning techniques on medical image processing/analyses

Deep Learning Approaches finds unique importance in the field of medical image analysis. Images pertaining to the measurement of various parts of the human body based on different scales like microscopic or macroscopic are coined as biomedical images. These biomedical images are generated through various instruments such as Ultrasound machines and CT scan images. Diabetic retinopathy, named as diabetic eye disease[6][7]. It is a problem occurs in many people who are suffering from diabetes.Diabetic retinopathy occures when small blood vessels leak blood and causes to the retina. in due course its lead to blindness.Diabetic Retinopathy Causes When glucose levels are too high for long duration it can damage tiny blood vessels that provide blood to the retina.Symptoms of Diabetic Retinopathy :Loss of central vision, Loss of cloudy and blurred vision, Reduced color vision, Instablity vision, Black or empty areas in vision.In this paper, we propose a technique of identifying and detecting diabetic retinopathy by extracting features from the digital fundus images. The proposed model makes use of Convolution Neural Networks for testing and validating the data set[8][9]. This further could be used for training the classifier and detecting whether the cell is benign or malignant. Rest of the paper consists of some related works proposed by various researchers, the methodologies and algorithms used in the proposed technique and experimental results

II. RELATED WORK

Various research works are proposed by different specialists for segmenting or classifying a specific object or a certain area from an image. Classification techniques used by numerous researchers for the classification of the tumor cells and hemorrhages. Some of the prominent research works for detecting and diagnosing various malignant cells using image segmentation techniques are mentioned in this section. A brain tumor as detected by Jason J. Corso in [17] by integrating segmentation with the Bayesian model. Weighted aggregation algorithm was used for the detection of tumor cells. The performance evaluation was done on a larger dataset where stochastic models were used to extracting the features. The model could be enhanced by providing an accurate boundary of the tumorcells. Concurrent image division and predisposition correction were performed by Kaihua Zhang [18], where minimization of energy was performed by an efficient Bayesian Learning Approach. The technique stated that the experimental results were carried out Standard Diabetic Retinopathy Database Calibration Level 0/1 (DIARETDB0/DIARETDB1) data- set [10], [11]. classified lung cancer images from CT scans using the MLFFNN technique yielding a good accuracy of 96.67%. FFNN approach used in [20], described the classification technique producing an accuracy of 92%. Rajesh Kumar Tripathy [21] combined SVM with Least Square and provided an accuracy of 95.34%. Persi et al [22] used the Particle Swarm Optimization technique for predicting heart disease yielding 92.2% accuracy. Ripon Mondal [23], proposed a mechanism for segmenting automated vascular tree segmentation using the Difference of Gaussian (DoG) filters. In [24] and [25], the authors have performed segmentation of blood vessels using various techniques performed on colored digital images.

III. PROPOSED APPROACH

Numerous feature extraction methods and classification techniques are used widely to identify and detect the location of the tumor cells and hemorrhages in a human body. Various classifiers such as SVM, K-means clustering and Decision Trees are used widely for the image segmentation applications are widely used in the existing mechanisms. In this paper, we majorly focus on the comparative analysis of various existing algorithms and the performance evaluation is done by using an application-oriented model. The enhanced and efficient model designed in the current paper first extracts the sequence of images from the scanner database. The images are then pre-processed where all the features of the images are extracted using convolution neural networks. The preprocessing is initially done by Medical Image Analysis where all the images are processed in such a way that it generates new fused images that have high quality when compared to the original images. These fused images are easier for training and classifying the classifier as it contains more spatial and spectral information. The validation of the dataset is done frame by frame for a particular time period. As the proposed model is an iterative process, the model tends to produce a more accurate result when compared with other existing classifiers. The various steps involved in the entire model is discussed as follows:

Image Acquisition: CT/MRI images obtained from patients suffering from diabetic retinopathy are collected from Databases and hospitals. The file formats collected from the database are of .jpeg, .tift, .png file formats and the file dimensions consist of rows and columns.

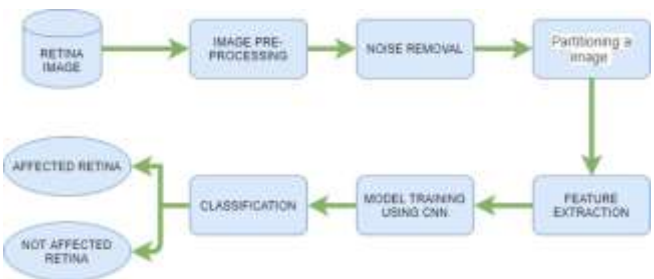

Fig. 1 Block Diagram of the Proposed System

Image Pre-processing Since the image we have used is a 3 dimensional, we add 512 * 512 slices filled with zeros to make all the cases of same length in the 3rd dimension. Then by using zero padding technique which is a pre-processing technique for CNNs, it consists in creating a frame of zeros around the image, so that all input image will have the same size[12].The CNN will then learn autonomously to ignore the zeros.There will be a change in the output image for the given input image. The occurrence of this change is due to the reduction of noise and/or enhancement of contrast. Image pre-processing is needed to vary its lightning condition.

Feature Extraction, for example, SIFT,SURF, BRISK, and so on are pixel handling calculations that are utilized to found focuses on a picture that can be enrolled with comparable point on different pictures. Initially a lot of these points are found - the expectation is that the calculation is size and rotationally invariant. Anyway on the grounds that you are managing discrete pixels, there is in every case some contortion. Next a lot of estimations dependent on the encompassing pixels is determined. The idea is that we can extraordinarily recognize little fixes in a picture. At that point we coordinate all the estimations on one picture with all the estimations on the correlation picture. When each point has discovered its best match, we dissect the arrangement of matches for correpondence[13][14]. The hypothesis is that if the correspondence is sound, you have a comparable picture. Divided picture which incorporates zone, border, comparable distance across, abnormality file, mean, standard deviation and entropy. Separated Features are utilized in a Neural classifier to prepare the model so that it could perceive a specific class as ordinary or unusual. The classifier will dole out the obscure article to the right class contingent upon the removed highlights.

Classification and Segmentation: In this process, the homogeneous regions are obtained from the input image. The regions of interest in an image are found by using the process of segmentation. It reduces the number of pixels of an image to make it easier for the next step of feature extraction and classification. Segmentation is tougher in digital fundus images as it is combined with a huge amount of data because of the extra dimensions that need to be considered for the neighborhood calculation. Fig. 1 depicts the flow chart of the entire classification process.

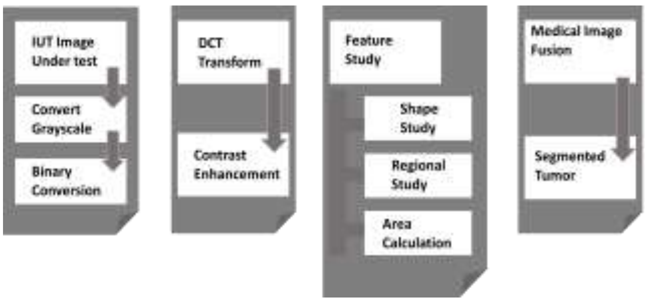

Fig. 2 Architecture Diagram of Proposed System

Fig. 2 represents the entire architecture of how the classification is done. The Input image is given from the scanner database and is first converted into Grayscale. The Discrete Cosine Transform is applied to the image when the contrast of the image is enhanced in such a way that even the small features of the images are perfectly visible. Then the features are extracted for further study and then finally Medical Image Fusion is performed on the image so as to obtain the segmented image. Once the fused images are obtained it is then trained using a neural network classifier that is responsible for extracting the features of the image[16][17]. The feature extraction is done using the CNN algorithm where all the features are extracted for further classification.

IV. EXPERIMENTAL RESULTS

The proposed research work is Carried out using a MATLAB tool which consist of image processing toolbox that help us in almost all phases such pre-processing, segmentation, classification with various Machine learning and Neural Network Algorithms.First, the input image from the scanner database is given to the tool. Fig. 3 is a sample input image obtained from a scanner database. When this image is passed the pre-processing takes place where all the features are extracted for further segmentation.

Fig. 3 Input Image

As the next step, the RGB components are extracted from the image and then converted to Grayscale image. Fig.3 shows the output image when the Grayscale filter is applied to the image.

Fig. 4 Filter Output

Both Fig. 3 and Fig. 4 are compared with each other to find the difference between the features and then Convolution Neural Network is applied to the images to identify diabetic retinopathy. The features are then trained with Neural Networks where some images are kept for training and the rest are kept for testing of images.

Fig. 5 Image Segmentation

The classifier learns the features and the successfully classifies when any new image is given to it. It identifies where the image is benign or malignant. Fig. 5 shows the identification of diabetic retinopathy from the image. The accuracy of the network is observed with 99.69% whereas 99.9% specificity and 80.48% sensitivity. The segmentation of the tumor from the exact image gives us various parameters for measuring such as its intensity, volume, and size. This helps in diagnosing and treating the tumor cells more effectively.

V. CONCLUSION

Diabetic Retinopathy is considered as one of the most upcoming challenges where more patients are likely to suffer. The detection of these hemorrhages at the initial stages could minimize the amount of risk in the medical field. In this paper, we have proposed an efficient method of diagnosing Diabetic Retinopathy at an earlier stage by using Medical Image Analysis. The digital fundus images obtained from CT/MRI scanners are used for extracting and segmenting the hemorrhages in such a way that generates high image quality. These images are then used for further classification. Convolution Neural Networks are used for detection and have obtained an accuracy level of about 99.69%. The future work can include the use of other deep learning techniques that can include the segmentation of the images based on the various other structural properties of the fundus and also which could reduce the computational time to a greater extent.

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