AUTOMATIC DETECTION OF SEVERITY GRADING IN DIABETIC RETINOPATHY USING CONVOLUTIONAL NEURAL NETWORK

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Abstract – *The primary reason for middle-aged people's eyesight is age is diabetic retinopathy (DR). Early identification of the development of diabetic retinopathy can be very beneficial for clinical treatment. Although several different feature extraction various strategies have been put forth, and the classification job for retinal images is still tedious and time-consuming even for those trained clinicians. Hence, primary screening of DR is to avoid vision loss, it is advised that diabetic patients have this procedure performed at least once a year. Recently, deep convolutional neural networks have manifested superior performance in image classification compared to previous handcrafted feature-based image classification methods. As a result, a Random forest classifier has been developed that can distinguish the intricate elements required for classification, such as micro-aneurysms, exudate, and hemorrhages on the retina, and then automatically deliver a diagnosis without human input. Last but not least, a CNN-based automated DR screening approach for retinal pictures is suggested. This method displays the different phases of DR (Mild, Moderate, and Severe) as well as its attention map for the region that is most affected. It also reduces the workload of ophthalmologists. Thus the proposed system of CNN classifier gives a significant improvement in terms of speed and accuracy when compared to previous methods.*

Key Words: **Diabetic retinopathy (DR) Fundus Images (FIs),micro aneurysm (MA), Flame-shaped haemorrhages (FSHs), Convolutional Neural Network(CNN)**

1. INTRODUCTION

Image processing is a form of processing images those are either captured as pictures or frames for which the input is given as an image and the output of the image processing is also a picture associated with the image[1]. Image processing refers to digital image processing but the visual and analog processing is feasible as well[2]. Medical Image Processing is in which the images generated from the human body for medical purposes are subjected to processing. It helps easily to detect and identify the disease[3]. Diabetic One of the main reasons of retinal degeneration (DR) is sightlessness and there subsist valuable behaviours that hold back the development of the disease provided that it would be identified in the early stage[4]. Normal retinal assessment of the diabetic patients guarantees an early identification of DR, which considerably reduces the occurrence of blindness[5]. Due to the high prevalence of diabetes, mass screening takes a lot of time and requires a large number of qualified graders to carefully examine the fundus images looking for retinal abnormalities. Diabetes and other disorders linked to aging and society are on the rise right now[6]. The issues relating to the eyes can be divided into two main categories. The first is eye disease, such as cataract, conjunctivitis, blepharitis, and glaucoma. The second group is categorised as lifestyle-related diseases, including diabetes, hypertension, and atherosclerosis. Diabetes can harm the eyes by damaging the retinal blood vessels, which can ultimately lead to visual loss. When diabetes is treated using prosthetic retinas, Diabetic retinopathy (DR) is the name used to describe this condition [7]. One of the treatments to reduce the amount of visual mutilation processed by DR has been identified as early detection and diagnosis, with a focus on routine medical examinations for the identification and supervision of this condition. During this method, retina images, also known as fundus images (FIs), are carefully processed using a medical imaging camera and are physically checked for the presence of DR objects by screeners and ophthalmologists. Diabetic Retinopathy is an eye condition that diabetes patients experience to a great extent. If a diabetic patient's blood sugar levels are too high, the blood vessels at the back of their eye will be destroyed, which prevents the retina from getting enough nutrients to adequately retain their vision [8]. One of the main reasons for visual loss worldwide is diabetic retinopathy, also known as DR [9]. It is one of the main causes of preventable blindness and vision impairment [10].The prevalence of DR among diabetic patients globally was found to be 7.62%–47.1% based on a meta-analysis of 35 studies from 35 different countries. The second category of DR severity is non-proliferative diabetic retinopathy. NPDR and proliferative diabetic retinopathy (PDR).There are three levels of NPDR: mild, moderate, and serious. Micro aneurysm (MA) and dot/blot haemorrhage (HA) are early stages of mild NPDR. As the illness advances, flame-shaped haemorrhage's (FSHs), cotton-wool patches, and hard exudates (HEs) In the moderate NPDR stage, (CWSs) become visible. Many more MAs, HAs, or venous beading (VB) arise in the severe NPDR stage[11]. The most advanced form of DR is called PDR. Neovascularization (NV), pre-retinal haemorrhage's (PHs), vitreous haemorrhage's (VH), and fibrous proliferation (FP), which is the source of tractional retinal detachment, are the important pathologies[12]. Early screening and diagnosis of DR in these diabetic people can stop vision loss and blindness. However, there isn't an ophthalmologist nearby in a remote rural region[13]. Consequently, an automation software is developed that can screen and DR with pathology extraction using algorithms for digital picture processing[14]. It is anticipated that this software will be a useful tool for medical professionals with limited expertise in DR diagnosis.

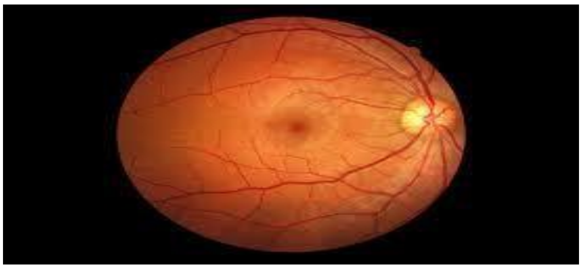

Fig. 1.1: Human Retina

Figure 1.1 illustrates the fundus image of a normal human retina. The retina is made up of a thin layer of light-sensitive tissue that is located close to the optical nerve. Light beams are concentrated onto the retina, where they are subsequently sent to the brain for interpretation of the images. The macula, a relatively tiny region, is located at the middle of the retina. The possibility of pinpoint vision is due to the presence of this macula that plays a major role in reading, writing or recognition of face[15]. The retina is in turn surrounded by peripheral retina. Without the presence of retina, efficient communication between the eyes and brain are not possible whereas only vision is possible through it.

Diabetic retinopathy typically affects both eyes. In the early stages of the sickness, those who are frequently affected by the disorder do not notice changes in their eyesight. But, when it worsens, it frequently has irreversible effects; including vision loss. Figure 1.2 illustrates the normal retina versus diabetic retina.

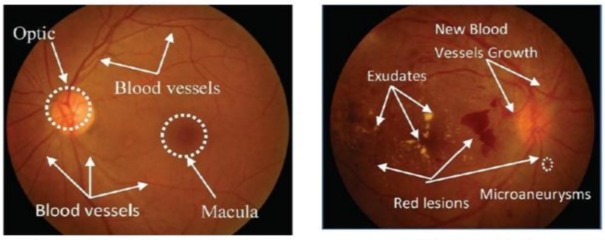

Fig. 1.2: (a) Normal Retina (b) Diabetic Retina

In the stage of diabetic retinopathy, blood vessel fluid leakage into the eye causes scarring of the retina. The onset of is the first sign of diabetic retinopathy. Haemorrhage in the retina[16]. The methods, algorithms, and techniques used to identify haemorrhage from retinal images of diabetic retinopathy are reviewed and explained. A fundus image-based algorithm based on a universal logical approach has been developed to detect the presence of Diabetic Retinopathy (DR) correlated lesions. It can distinguish between red and bright lesions and does not require any special pre- or post-processing. Several actions are carried out, and coloured retinal images are used to assess the various stages of diabetic retinopathy[17]. Micro aneurysms, which resemble small, secular pouches and look as tiny red dots, are brought on by a localised enlargement of the capillary walls. Another idea contends that the walls are brittle and prone to shattering, which might result in haemorrhages. Hard exudates are yellow lipid deposits that appear as vivid yellow lesions. The light, spherical region known as the optic disc is where the blood vessels initially develop. Visual acuity is greatest in the fovea, the central region of the retina. A mixture of interior components of microaneurysm detectors including macular centre and retinopathy-related lesion detection using specifically pre-processing methods and applicant extractors are proposed[18]. The earliest stage of the illness is non-proliferative diabetic retinal disease, where the retinal blood vessels leak fluid or bleed. In NPDR, the arteries in the retina turn out to be very weak and they tend to be very minute and dot like haemorrhages will be seen. These types of weak blood vessels generally tend to swell or cause edema in the retinal image and it results in decreased vision. The symptoms of this disease will be mild or non-existent. Micro aneurysms, haemorrhages, hard exudates, macular edoema, and macular ischemia are alterations brought on by NPDR that affect the eyes. Proliferative diabetic retinopathy (PDR) is now present since the illness has advanced to that point. PDR causes circulation problems, which make some parts of the retina ischemic or oxygen-depleted. New blood vessels become part of the circulatory system that helps the retina maintain enough oxygen levels[19]. Neovascularization is the word for this. Blood may enter the vitreous and retina, causing spots or floaters that are consistent with visual loss. SDR causes aberrant vascular growth and scar tissue, which can be major difficulties for glaucoma, immediate retinal detachment, and gradual vision loss.

1.2. Symptoms of Diabetic Retinopathy

Certain symptoms of diabetic retinopathy identified by the research community are the observation of spots, dots or cobweb-like dark strings floating in the vision of the patients. Some patients experience hazy vision and a cyclical change in their eyesight from blurry to clear. Some patients may experience black or dark spots in their field of vision in addition to having impaired night vision, which can ultimately lead to visual loss[20]. The retinal vessels are connected for a few more reasons. According to reports, this happens when the blood capillaries in the retina change, impacting diabetes patients and even leading to eyesight loss. On certain cases the patients with retinal vessels suffer swelling and also observe leak fluid that cannot be reversed affecting the patients in large.

2. METHODOLOGY AND ALGORITHMS

2.1 Modules

2.1.1. Pre-processing

i. Augmentation

Augmentation can add randomized rotations to input images so that a network is invariant to the presence of rotation in input images.

Input : Retinal fundus image

Output : Augmented images

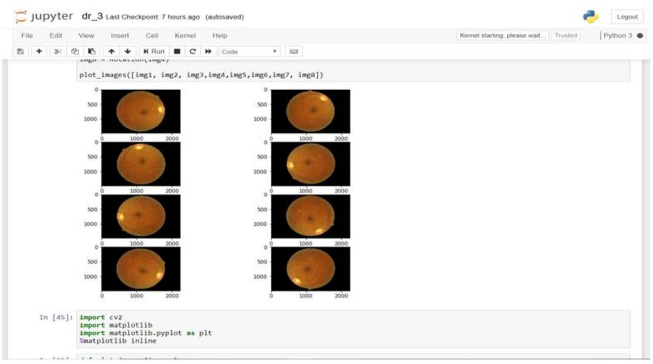

Figure 2.1.1: Augmentation of retinal image

ii.Resize and Normalize

Image resizing increases or decreases the total number of pixels.

Normalization is a process that changes the range of pixel intensity values.

Input: Augmented images

Output: Resized image

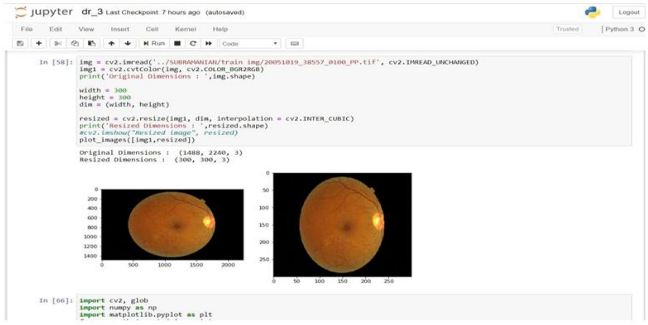

Figure 2.2.2: Resizing of retinal image

2.1.2. Segmentation

The tiny, elongated structures in the retina are blood vessels. By segmenting blood vessels in retinal images, early illness identification is made possible. Automating this process has various advantages, including reducing subjectivity and removing labor-intensive steps. The optic disc, which represents the beginning of the optic nerve, is where the fibres of retinal ganglion cells converge. At the optic disc, the retina's major blood arteries also enter. The fovea, a 1.5 mm broad depression on the internal surface of the photoreceptor layer, is made entirely of cone photoreceptors and is tailored for the best possible visual acuity. The 0.5mm-diameter foveal avascular zone is a region inside the fovea (An area without any blood vessels).

Input: Resized image

Output: Image segmented with Blood vessel, Optic disc and Fovea

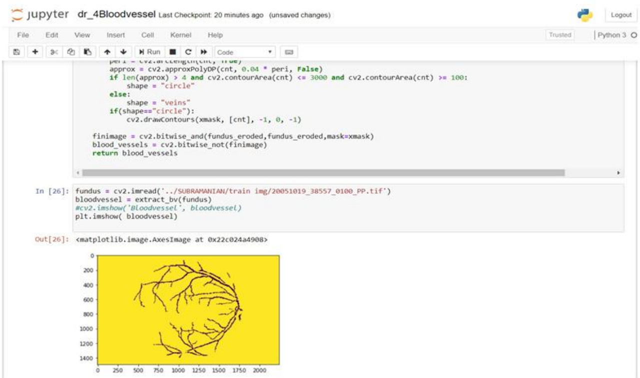

Figure 2.2: Extraction of blood vessel from retinal image

2.1.3. Classification

The final test item class is then chosen by averaging the votes from numerous decision trees from a randomly chosen portion of the training set.

Input : Segmented Images

Output: Image with diseases (MA, Haemorrhages, Exudates)

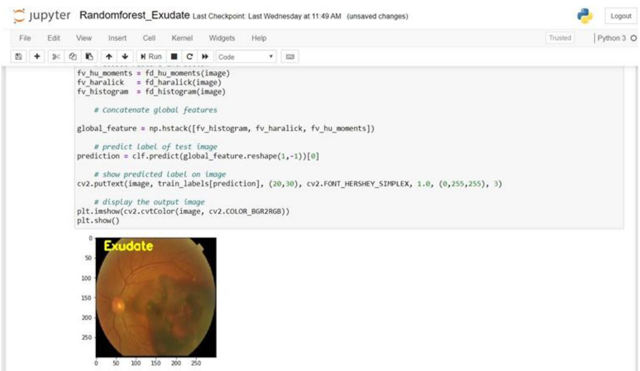

Figure 2.3: Detection of Exudate disease in retinal image

2.1.4. CNN Classifier

Convolutional neural networks are one sort of artificial neural network (CNN). It employs perceptron, a technique for supervised learning, to examine data. Each individual neuron takes in a variety of inputs, weighs them, and then sends the weighted result through an activation function to produce an output.

Input: Image with disease

Output: Image classified based on severity of MA

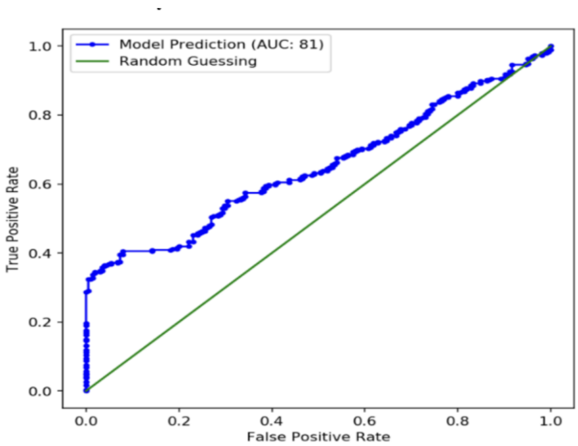

Figure 2.4: Accuracy of CNN classifier

3.1 SYSTEM ARCHITECTURE

This chapter discusses the overall system architecture and detailed description of all modules.

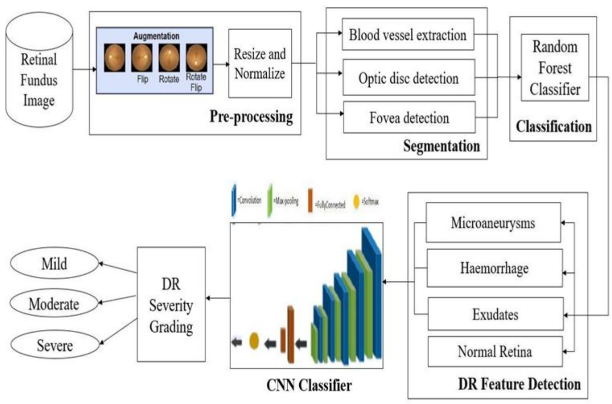

Figure 3.1 System Architecture

Figure 3.1 describes the overall system architecture of the proposed DR detection with its severity from Retinal fundus images. This system starts with the pre-processing stage where augmentation, resizing and normalization of retinal images is done. Several segmentations, including blood vessels, the optic disc, and the fovea, are found in the pre-processed images. Using a random forest classifier, the DR features are found in these segmented images. Finally for each DR feature detected the severity of the disease is calculated using the CNN classifier for better accuracy.

3.3 ALGORITHM

The Machine Learning system uses test data to assess the predictive accuracy of the trained model and training data to train models to recognize trends. By comparing predictions on the evaluation data set with actual values (also referred to as ground truth) using a variety of measures, machine learning systems assess their predictive performance.

- Random Forest
- Convolutional Neural Network (CNN)

3.3.1 Random Forest

This model employs two crucial ideas that give it the name random rather than averaging the predictions of trees, which are referred to as the "forest"

- selecting at random from training sets when creating trees

- Random feature groups are taken into account when splitting nodes

3.3.2 Convolutional Neural Network (CNN)

CNNs essentially employ very little pre-processing when in comparison to alternative picture classification methods. CNN is able to learn the rules that other algorithms require to be manually created. Input, output, and hidden levels are all present in CNNs. Convolutional, ReLU, pooling, and completely connected layers typically make up the hidden layers. An image, which is a matrix of pixel values, serves as the input. Consider that the input matrix reading begins in the upper left corner of the image. Following that, the algorithm selects a filter, which is a smaller grid. (Or neuron, or core, or whatever). The filter then produces convolution as it processes the input image. It increases the filter values by the starting values of the pixels. These segments are multiplied as a whole. At the conclusion, one number is obtained. The filter moves one unit to the right each time it completes an action of a similar nature because it has only scanned the picture in the top left corner. The filter acquires a matrix after going through every position, but it is smaller than the input matrix. The nonlinear layer is added after every convolution operation. Through a process referred to as activation, it introduces nonlinear properties. A network wouldn't be robust enough to symbolize the response variable without this feature. (As a class label). The pooling layer follows the nonlinear layer. Pooling layers would result in fewer parameters when the pictures are too large. Spatial pooling, also referred to as subsampling or down sampling, reduces each grid's complexity while maintaining important data. There are three different kinds of geographic pooling: Max Pooling, Average Pooling, and Sum Pooling. As a result, the pooling layer performs a down sampling process on the image's width and height. The picture volume decreases as a consequence. This means that if some features (such as boundaries) were previously identified in the convolution process, a detailed image is compressed into less detailed images. Before adding a fully connected layer, all convolutional, nonlinear, and pooling layers must be completed. The raw input of the convolutional networks is used in this layer. When a fully connected layer connects to the network's endpoint, N classes are created from which the model chooses the desired class.

4. RESULT AND DISCUSSION

Image detection for effective identification of diabetic retinopathy is to discover the problem related to diabetes that can lead to sightlessness if not cured at its preliminary stages. Even though this research has complex recognition of DR lesions from retinal images, the effortless occurrence of any lesion is not sufficient to choose on the requirement for recommendation to a patient. The computerized transmission for Diabetic Retinopathy (DR), a common complication of diabetes, faces a significant challenge in the identification of micro aneurysms in digital color fundus images. Numerous methods were available in the past to accomplish this recognition, but none of them had ever been compared to one another on the same set of data.. Towards the recognition of DR, since micro aneurysms (MAs) are the earliest stage of the illness, it is crucial to classify them to determine whether or not they exhibit retinopathy symptoms. A novel supervised algorithm for recognizing blood vessels visible in retinal images is presented, which employs a Neural Network (NN) model for pixel classification and evaluation of a 7-D vector made up of features based on moment invariants and grey levels for pixel representation. Another method presents the outcome of the microaneurysm recognition prepared in the circumstance of the Retinopathy Online Challenge (ROC), for different features of DR detection. Scientific interest lies in another unique method known as the regular MA recognition from digital colour fundus images, which acts as an early indicator of diabetic retinopathy and their typical recognition from colour retinal images. Diabetic retinopathy is a condition that affects millions of individual's worldwide (DR).Thus an automatic mechanism to identify the presence of DR along with its severity by evaluating the photograph of the central field of the retina has been developed. Selected pre-processing techniques are carried out for Micro aneurysm discovery, which is crucial in grading diabetic retinopathy, after digital fundus pictures revealed diabetic retinopathy. All recent works have assumed that Visual Dictionaries for Automatic Retinal Lesion Detection entails the development of an automatic DR screening system capable of detecting the presence of many DR-related abnormalities. The previous points of interest and visual dictionaries methods of each specific lesion are identified and they detect the automatic retinal lesion, increasing its accuracy rate. But, if the level of specific lesions is increased, then the detection of automatic retinal lesions will become a complicated process which reduces its accuracy rate. In addition, the detection time becomes complex and increases. The present study is conceived with automatic diabetic retinopathy detection technique from fundus images. In addition, it also smoothens the detection technique to avoid complexity and confirm a higher accuracy. This verifies better accuracy and offers efficient detection at a higher level of sensitivity. Finally, the suggested approach employs deep convolutional neural network models that rank the severity of DR in fundus images in order to diagnose the presence of DR and offer pertinent advice to DR patients. The goal is to use a deep convolutional neural network to assess the severity of diabetic retinopathy. The goal is to use training datasets to train the algorithm. Every day, more people are diagnosed with diabetic retinopathy. Despite mounting proof of the value of routine DR screening and early intervention, it frequently results in poor vision function and is the main cause of blindness. Due to insufficient medical care, it has frequently been neglected in the health care system and in many low-income nations. A system that will provide predictions about diabetic retinopathy is built because there aren't enough methods to detect the condition.

5. CONCLUSIONS

The proposed system assesses the severity of diabetic retinopathy in a patient using digital image processing techniques on fundus images. In the proposed study, a computer-based approach is employed to assess the degree of DR using a CNN classifier, and the results show that DR can be discerned rather well from fundus photographs. It can be used as a substitute or supplemental instrument for DR screening, particularly in remote locations where ophthalmologists are scarce or in rural areas where ophthalmologists are overburdened with patient cases. In order to increase the DR classification's accuracy, extra digital image processing methods or other deep learning and artificial intelligence-based techniques may need to be developed in software. Sensitivity, Specificity, and Accuracy performance parameters exhibit better performance when compared to values determined by human observers for these parameters. The outcome demonstrates unequivocally that the suggested approach is successful in identifying severity in DR images. The proposed method has an accuracy of 81%.

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