Detection of Diabetic Retinopathy for IT sector using CNN and ResNet50 models

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***Abstract*— Due to digitalization, the software sector has grown significantly since the corona virus outbreak. Up to 2017, there were over 2.75 million software engineers available in India. Nonetheless, this figure will rise to 5.2 million by 2023. When they use a computer for extended periods of time, the majority of software developers experience eye sight issues. In India, there are currently about 80 million people with diabetes, and by 2045, this can be projected to be 135 million. The software engineer's eye sight issues could be more severe if they also have diabetes. Diabetic Retinopathy is the condition that results when a person has both diabetes and poor vision. Diabetic retinopathy affects about 30% of diabetes patients. The majority of people in the working age group around the world are affected by diabetic retinopathy, which is the greatest frequent factor of preventable loss of vision. In order to quickly identify, diagnose, and treat diabetic retinopathy before it worsens, we intend to create a deep learning model to do so. By extracting two features from retinal images Micron way, which is discovered to be the first symptom-showing feature, and Hemorrhage, which exhibits symptoms of further stages this seeks to discover the disease at the earliest stage feasible.**

I. INTRODUCTION

There are several issues with diabetes, one of which is diabetic retinopathy, which affects the eyes. It can cause total blindness and vision loss in severe cases. Some among the first signs of diabetic retinopathy include eye floaters, fuzzy vision, darkened portions of eyesight, and difficulty seeing color. If you want to avoid going blind, you must correctly diagnose diabetic retinopathy in its early stages. Tiny red spots can be seen in the retina during the earliest phases that is non-proliferative. Those tiny patches might be hemorrhage, irregular blood vessel pouching might be microaneurysms. The linings of these blood arteries are vulnerable to damage, allowing fluid and fatty material known as exudates to spill out. Diabetic retinopathy can be diagnosed using pupil enlargement, a visual acuity screening, CT using optical coherence, and other physical exams. Yet, they are time-consuming and painful for the patients. Deep learning falls into the subclass of machine learning which is basically a 3- or many- patterned neural network. In order to learn from vast volumes of data, artificial neural networks attempt to simulate that how individual brain processes. Although a network just with a single level would generate approximations, additional hidden layers would improve tune and maximize overall efficiency. Deep learning is the motivating factor behind several AI services and programs that enhance mechanization via performing mental and mechanical activities without human involvement. CNN is a deep learning strategy that can recognize data with a grid layout, such as photographs. CNN was designed with the animal visual brain in mind, and it is intended to gain spatial feature ordering, patterns that vary from basic to high standard, instantly and flexibly. A traditional CNN is made up of 3 sorts of layers: convolution, pooling – to extract features, fully connected layer - moves these extracted features into the output.

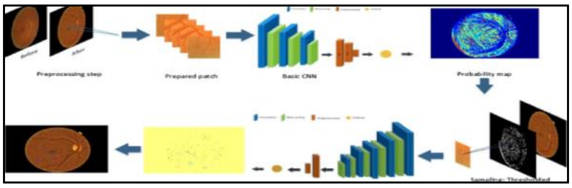

Fig.1.1. Step wise process of CNN

In order to perform color normalization and remove retina background, a pre-processing procedure is necessary since retinal pictures are typically not equally lit. By calculating the backdrop picture and deducting it from the actual image, this step was completed. The prepared patch is fed into the convolution, max pooling, and fully connected layers of the fundamental CNN. The probability map over which selection is conducted and which is used as input by CNN to create the desired output is the produced output.

$$\mathbf{Z = W^T . X + b}$$

Where, Z is the output, W is the weight matrix, X is the input matrix and b is the bias.

The above equation shows the mathematical equation of CNN where W is the weights matrix, X is the input data and b is the bias matrix.

II. LITERATURE REVIEW

Diabetes morbidity necessitates the screening of millions of people for diabetic related retinopathy. Deep neural networks provide a significant benefit in the recognition of diabetic retinopathy through optical pictures by enhancing the detection of diabetes-related retinopathy abnormalities and adverse outcomes of diseases. Large volumes of data have been produced as a result of the remarkable advancements in biomedical research[1]. The worldwide council of ophthalmology has advised categorizing diabetic retinopathy into five stages with varying risks of advancement. The blood vessels in the retina are impacted by this issue because they undergo many alterations due to several metabolic disorders. Impact to the capillaries of the blood arteries results from the deficiency of pericytes, which are flexible neurons that encircle vascular cytoplasmic membrane in the body's venules. Ischemia, a disease that occurs when there are extra molecules of glucose in the circulation and they block blood flow by congealing inside the capillaries, is what causes this damage. Microaneurysms are congenital restorations of the retinal capillaries' arterial ends, which are brought on by the narrowing of these blood arteries, which results in a reduction of blood flow. This process makes the arteries less impermeable, which might result in breaches like ruptures or lipid sweating[2]. Diabetic retinopathy caused 2.6 million people are visually handicapped or blind in 2015, and the figure is expected to climb to 3.2 million by 2020. Although retinopathy is predicted to become less prevalent in wealthy nations, low- and mid- nations must prioritize early identification and treatment of the illness. Researchers have demonstrated that computerized retinopathy diagnosis and evaluation reduces time and labor because of the current advancement of deep learning[3]. It takes a lot of time and requires professional personnel with extensive knowledge in identifying this eye ailment from computed tomography and other criteria to manually diagnose this medical picture. When qualified medical professionals make the diagnosis, it also becomes a costly one. Also, because to human limitations, only a specific number of clients may be attended to simultaneously. The technique is also vulnerable to human mistake, which can occur often throughout various doctor-performed medical diagnosis processes. Hence, the need of receiving a second opinion is often emphasized for people who have been given a critical medical diagnosis. Owing to all of these drawbacks, automating this process would, if it were possible, save costs, decrease diagnostic mistakes, and accelerate the procedure to allow for the continuous processing of several patients[4]. Medical imaging is helpful in learning more about the interior organs of the human body. Once it has been gathered, medical procedures including diagnosis, treatment, and analysis are made simpler and more effectively carried out. There are several methods for obtaining information on the human body in picture formats, depending on the body part or potential treatment area. Doctors and professionals utilize it for therapies, analysis, and even to gain experience in the diseases[5]. All people with diabetes, regardless of the type, require routine yearly retinal screenings for the prompt identification and appropriate management of diabetic retinopathy. Traditionally, ophthalmologists do fundus examinations to check for retinopathy, pharmacists use conventional endoscopic cameras to take color fundus photographs[6]. Abrasive secretions cause bright yellow patches to develop on the retina as a result of plasma leakage. They have angular boundaries and are found in the exterior regions of the retina. The expansion of the nerve fiber results in delicate secretions, commonly referred as cotton wool stains, which are white blotches on the retina. It is shaped like an oval or circle[7]. Deep learning of computed tomography is a workable and economical method for the systematic evaluation and detection of severe diabetic retinopathy. A convolutional neural network method was shown to enhance detection effectiveness for referable DR from fundus images[8]. Telemedicine now routinely uses retinal image processing to automatically classify ophthalmologic disorders. Earlier, segmentation was done manually, although it proved challenging, laborious, and demanded a substantial amount of knowledge. But, computer-assisted eye disease identification is comparably more affordable, feasible, and determined to accomplish their goals, and it does not necessitate a highly qualified physician to grade the photos[9]. We are considering the prospect that the DR connected to diabetes would emerge to be a heavy concern for medical experts regarding the duration and effort required take care for these increasing numbers as the prevalence of diabetes continues to rise around the world. The approach to easing some of the costly strain chronic sickness places on the society and medical system may be mechanization of the most monotonous tasks[10].

III. METHODOLOGY

A. Dataset:

The dataset named “APTOS 2019 blindness detection” is used which comprises of 3662 images. These images are taken by the Aravind Eye Hospital technicians from the rural areas using fundus photography.

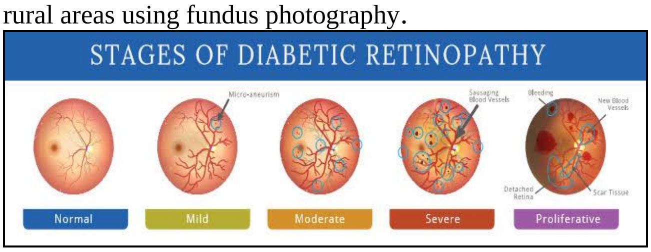

Fig.3.1. Different stages of severity of diabetic retinopathy

Stage 0 – No DR, Stage 1 – Mild, Stage 2 – Moderate, Stage 3 – Severe and Stage 4 - Proliferative DR.

The dataset contains a file named train.csv which consist of id_code and diagnosis. id_code is the name of the image and diagnosis shows the stage of the disease.

Table.3.1. The data in the train.csv file

	id_code	diagnosis
0	000c1434d8d7	2
1	001639a390f0	4
2	0024cdab0c1e	1
3	002c21358ce6	0
4	005b95c28852	0

B. *Preprocessing:*

The RGB image is transformed into the HSV image during preprocessing.

C. *Classification:*

Before classification, the dataset is increased by data augmentation, which includes modifications including rescaling, rotation, and flipping. Eventually, the CNN model's ResNet50 is used for classification.

D. *ResNet50:*

The residual network, was a key improvement in neuromorphic development for challenges with computer vision. Whereas the basic Resnet contained 34 layers, highly complicated versions, such as the Resnet50, incorporate 3-layer bottleneck blocks. Resnet50 is a configuration that may execute with 50 levels. Because of concerns about time, the construction block was redesigned into a bottleneck to develop the layers. This level used a stack of three rather than the earlier ones. ResNet-50 is the name of a CNN with 50 layers. It is a catch-all term for a kind of neural network that operates as the framework for most of the computer vision applications. The main innovation of ResNet was its capacity to train incredibly intricate computational models with over 150 layers.

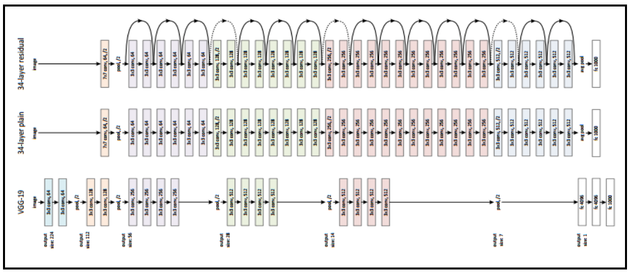

Fig.3.2. Process of ResNet

The above Fig.3.2 is a 34-layer simple network with shortcut connections or skip connections added, with an architecture modelled after the VGG-19. Through the inclusion of skip connections or residual blocks, the architecture is further changed in the image above into a residual network.

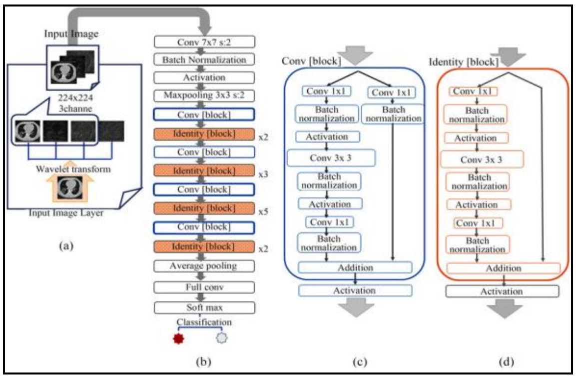

Fig.3.3. Architecture of ResNet50

(a)An input layer for 3-channel images. (b)A general overview of ResNet-50's organizational structure. (c)The configuration of a convolution block with variable input dimensions. (d) The design of an identity block with constant input dimensions.

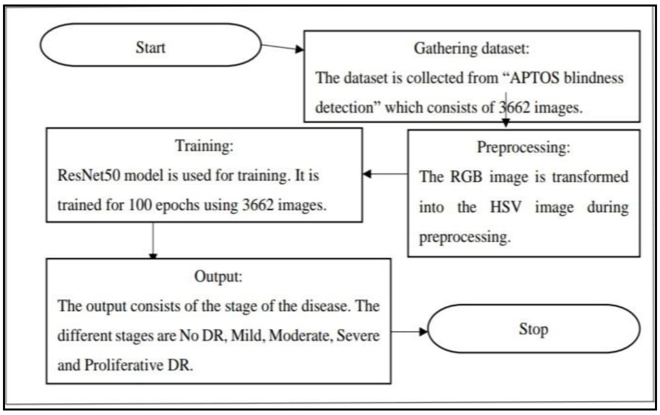

Fig.3.4. Flowchart of the methodology

IV. RESULTS

A. *Case-1:*

The given input is:

Fig.4.1. Retina of a person

The above Fig.4.1 is taken from a diabetic person who is suffering from blurred vision.
The output is: 4 – Proliferative DR

B. *Case-2:*

The given input is:

Fig.4.2. Retina of a person

The above Fig.4.2 is taken from a diabetic person who is suffering from rapid increase of sight.
The output is: 2 – Moderate DR

C. Case-3:

The given input is:

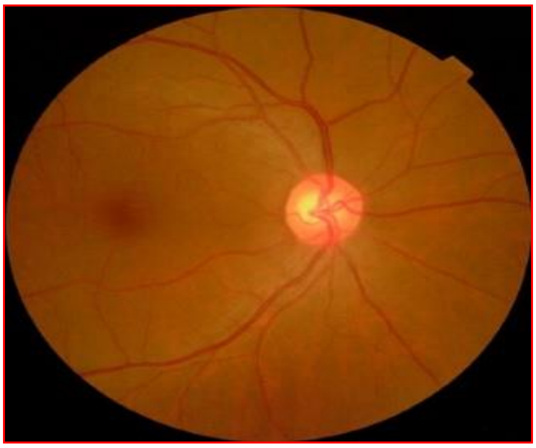

Fig.4.3. Retina of a person

The above Fig.4.3 is taken from a diabetic person who does not have any eye problem.
The output is: 0 – No DR

D. Case-4:

The given input is:

Fig.4.4. Retina of a person

The above Fig.4.4 is taken from a diabetic person who is suffering from increase in eye sight.
The output is: 3 – Severe DR

V. CONCLUSION

In this project, we employed CNN for retinal image categorization using the ResNet50 model, which enhances the categorization of microaneurysms and hemorrhage and classifies the phases of illnesses. It will take a lot of time for medical professionals to study and find diabetic retinopathy using retinal images using laborious manual approaches. So, an automated system can considerably minimize the labor required for diagnosing big numbers of retinal images, and we can acquire the results faster so that the treatment can begin earlier. Large numbers of retinal images can also be processed faster, which lowers the cost.

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