ISSN (Online): 2583-7052

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 02(11), November 2023, pp. 16-28

Article Title: Implementation and Prediction of Diabetic Retinopathy Types Based on Deep Convolutional Neural Networks

Implementation and Prediction of Diabetic Retinopathy Types Based on Deep Convolutional Neural Networks

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ABSTRACT

Diabetic retinopathy (DR) is the primary cause of preventable blindness in those within the working age group in developed nations. The macula, optic discs, and blood vessels that make up a healthy retina are irregularities that indicate a true eye condition. Therefore, retinopathy detection is crucial. Therefore, this study suggests using deep convolutional neural networks to build and predict different kinds of diabetic retinopathy. A pre-processing approach first initiates the input picture. The spatial processing method known as the Gaussian filter, which reduces picture noise and increases the clarity of fuzzy pictures, handles this procedure. The picture is sent to the regions for segmentation in the next stage. The size and form of the illness may be precisely determined using fuzzy C-means (FCM) segmentation. Additionally, it attempts to maintain as much difference between the clusters as well as much similarity between the intra-cluster data points. The next phase in the process is to use deep convolutional neural networks (DCNN). In order to extract features from the input picture, the convolutional layer applies filters. To expedite computation, the pooling layer samples the picture; the fully connected layer then generates the final prediction. The early detection of diabetic retinopathy has been made easier by the use of DCNN algorithms. Within the domain of medical image processing, the DCNN algorithm represents a methodically ordered approach and it shows 94.7%. This work offers a high degree of sensitivity and precision in identifying whether a picture has diabetic retinopathy or not. Creating the output image is the final stage. Python Google Colab software is used in the implementation of this paper.

Keywords: Diabetic Retinopathy (DR), Gaussian Filter, DCNN, FCM, Python.

1 Introduction

According to estimates from the World Health Organisation (WHO), 422 million persons globally had diabetes in 2014. Diabetic retinopathy (DR) is an ocular condition that is linked to chronic diabetes. More than 60% of those with type 2 diabetes and almost all those with type 1 diabetes have DR. Once DR has advanced, visual loss is frequently irreversible even though up to 98% of severe cases can be avoided with early identification and treatment. A skilled

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doctor must often review digital colour fundus photos of the retina in order to diagnose the severity scales, which is a laborious manual procedure that takes time. Inspired by this, we develop a supplementary system based on deep convolutional neural networks (DCNN) to facilitate the early screening of DR by doctors, therefore accelerating the process of identification and reducing the risk of visual loss related to the condition [1-4].

Because of its effectiveness in handwritten character recognition tasks, convolutional neural networks (CNN) gained popularity in the 1990s. However, when support vector machines (SVM) gained popularity, CNN's use declined. By demonstrating a notable increase in image classification accuracy on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012, sparked renewed interest in CNN. Since then, CNN and DCNN have become extensively used and have continued to achieve new breakthroughs in a variety of image analysis domains, such as segmentation, classification, and medical image analysis [5-7].

The creation of handmade characteristics, which is sometimes complex, is the foundation of early DR detection research. CNN-based techniques have recently greatly increased the accuracy of DR detection. Zoomin-Net was introduced by Wang et al. to address simultaneous localization and classification difficulties. The aforementioned techniques need to be adjusted for new testing datasets with distinct grading rules, such as the Messidor dataset. It is necessary to use methods like SVM with linear or RBF kernel on top of the characteristics that were taken out of their suggested network. For huge datasets, the fine-tuning procedure would be prohibitively costly or perhaps impossible. Furthermore, the aforementioned techniques make advantage of intricate networks [8-10].

This paper suggests using DCNN to build and predict different kinds of diabetic retinopathy. A pre-processing approach first initiates the input picture. The spatial processing method known as the Gaussian filter, which reduces picture noise and increases the clarity of fuzzy pictures, handles this procedure. The picture is sent to the regions for segmentation in the next stage. The size and form of the illness may be precisely determined using FCM segmentation.

2 Proposed System

The whole DR detection mechanism is depicted in Figure 1. The pre-processing stage, segmentation, and the classification network are its three main parts. The area of interest (ROI) detection and image enhancement processes comprise the second division of the pre-processing stage. The gaussian removes irrelevant data, and the picture enhancement highlights characteristics like haemorrhage and micro aneurysms that are pertinent to symptoms of DR. The goal of the classification network is to categorise the DR severity scales. Ultimately, the post prediction effectively addresses the issue of disparate DR grading systems.

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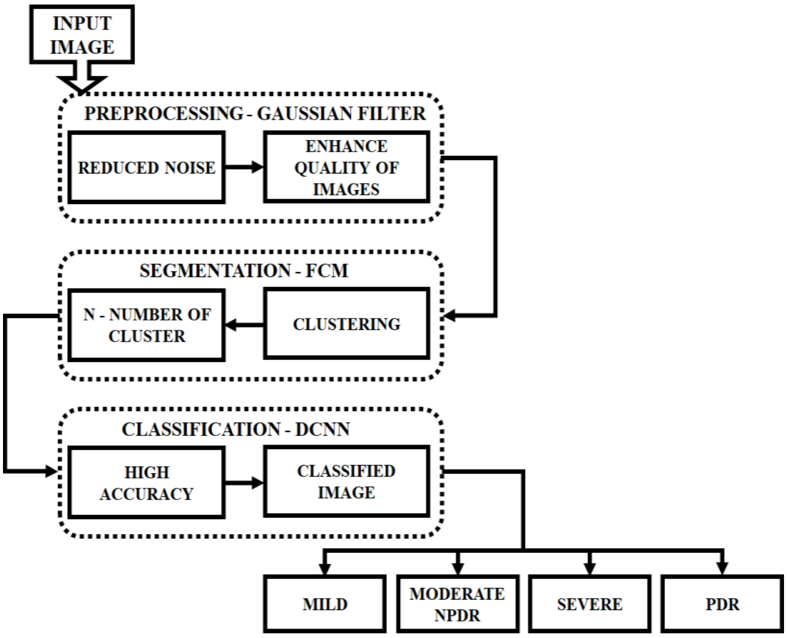

Figure 1: *Proposed System*

The suggested work predicts the forms of diabetic retinopathy using a deep convolutional neural network technique. The block diagram of the suggested system is shown in Figure 1. The Gaussian filter, which reduces noise and improves the appearance of blurry pictures, may be used to analyse the input image during the first preprocessing step. Fuzzy C-means segmentation is used to handle this modulus's segmentation step after preprocessing. This procedure maintains the greatest degree of diversity among the clusters and is employed to precisely ascertain the dimensions and configuration of the illness. The following deep learning classifier approach is acceptable for the segmented picture. Deep convolutional neural networks are used in the deep learning classifier approach (DCNN). Three distinct kinds of layers comprise the DCNN classifier. The first convolutional layer is applied to the segmented image in order to gather features. The fully connected layer on the third layer provides the final prediction, and the second pooling layer samples the image to expedite processing. Furthermore, the DCNN classification offers superior sensitivity and specificity in identifying whether an image has diabetic retinopathy or not. Creating the output image is the last stage.

2.1 Image Preprocessing by Gaussian filter

The primary issue with diagnosing DR at different phases is the presence of overlapping symptoms, meaning that a mild symptom may also be evident in a moderate stage as well as to the moderate specific symptoms. This complicates classification, particularly in the later stages. Despite geometric changes to pictures, pre-processing seeks to enhance the image data by reducing undesired distortions or emphasising specific visual features that are crucial for

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further processing. The Gaussian filter is used to pre-process the incoming dataset. The term "image processing" describes the use of algorithms or quantitative analysis to digital picture data. Improving the identification of aberrant brain tissue is a typical objective of image processing techniques used in neuroimaging. Algorithms used in image processing often include segmentation, noise reduction, edge sharpening, edge detection, and contrast enhancement. These methods automate or partially automate the manual illness detection procedure. Digital image processing enhances image quality by eliminating noise. Gaussian filters are used in image processing to eliminate noise. It covers robotics, medical image processing, radar and sonar image processing, and satellite-based remote sensing data. It was now feasible to alter multi-dimensional signals thanks to modern technologies.

Gaussian filters are the most often used smoothing filters. These filters are very helpful as edge and line detectors and have been demonstrated to have a significant function in identifying edges in the human visual system. A low pass filter called a Gaussian filter is used to blur certain areas of a picture and minimise noise, or high frequency components. This filter is constructed as an Odd sized Symmetric Kernel (DIP version of a Matrix) that passes over each pixel in the Region of Interest in order to produce the desired effect. It is applied to ultrasound pictures to eliminate speckle noise. The noisy pixel in the picture is replaced by the average value of the surrounding or neighbouring pixels, which is based on a Gaussian distribution. When removing speckle noise from ultrasonic or MRI brain pictures, a Gaussian filter is used. With this method, the noisy pixel in the image which is based on a Gaussian distribution is replaced with the average value of the surrounding or nearby pixels.

External influences and light intensity are the causes of blurred noise. Using a hand-held camera to take decent pictures in low light may be a frustrating experience. The pictures are frequently grainy or noisy. Blurred noise is the term used to describe these types of photographs that have fuzzy, blurry pixels. Image restoration is the practice of attempting to eliminate noise from an image and return it to its original quality. By restoring the pixel value, this is a crucial component in preserving the image's quality. Restoration methods are the reverse of picture deterioration, serving as a paradigm for linear image degradation. The concept of goodness is a mathematical tool used in restoration techniques to assist produce the best estimate of the intended outcome.

2.2 Fuzzy C-Means Algorithm

The process of dividing a picture into several subgroups, or pixels, known as picture Objects is known as segmentation. The segmentation process in this system uses the Fuzzy-C-Means method, which lowers the image's complexity. The first step in the procedure is to analyse the input picture so that the model can determine whether the mole is malignant. Prior to any further processing, the image is transformed to the HSV format. Segmentation and grouping using Fuzzy C Means are used. One popular model for clustering is the fuzzy C-means

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clustering technique. The members' distances are assigned using this manner based on the cluster centre. Usually, an inverse relationship is formed. A single data point in this approach can be allocated to many groups with different membership grades. This technique is frequently applied to pattern recognition. Because an eye lesion is darker than its surrounding area, just that area will be taken into consideration for further processing once the picture has automatically been separated into several colours. Popular data clustering technique fuzzy c-means algorithm (FCM), sometimes called fuzzy ISODATA, assigns a membership grade to each data point indicating how much it corresponds to a cluster. FCM partitions a collection of n vectors, X $_j$, j = 1, …. ,n, into c fuzzy groups, and finds a cluster center in each group, such that a cost function based on a distance measure is minimized. The fuzzy clustering takes into account the overlapping of the clusters and allows partial belongingness of the object to all clusters. In other words, a given data point can belong to any group with a degree of membership between ° and 1.

The procedure is an iterative clustering technique that minimises the weighted within group sum of squared error objective function J FCM in order to get an optimal c partition. The fuzzy c-partition that arises from a fuzzy clustering is represented by the following equation.

$$J_{FCM} = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^q \, d^2(x_k, v_i) \quad (1)$$

Where X = {x1, x2, · · ·, xn} ⊆ R p is the data set in the p-dimensional vector space. ,n is the number of data items, c is the number of clusters with 2 ≤ c < n, u_{ik} is the degree of membership of x_k in the i th cluster, q is a weighting exponent on each fuzzy membership, v_i is the prototype of the Centre of cluster I, $d^2(x_k, v_i)$ is a distance measure between object x_k and cluster Centre v_i.

An algorithm that iteratively finds the best solution in FCM has been developed. The fuzzy clustering paradigm is implemented by the FCM algorithm. It changes membership degrees in a way that reduces within-cluster variation fuzziness. The most often used technique for multiclass membership value assignment to pixels in image processing is FCM. After each class's (cluster's) memberships for data points, such as pixels, are known, we may assign pixels to the class with the highest membership. The fuzzy c-mean approach does not require an initial set of training data, making it unsupervised in terms of producing membership functions for processing afterwards.

2.3 Deep Convolutional Neural Networks

The form of neural network most frequently used to find patterns in pictures and videos is called a deep convolutional neural network (CNN or DCNN). DCNNs are a development of classic artificial neural networks that use a three-dimensional neural architecture modelled after an animal's visual brain. Applications such as object identification, picture classification,

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recommendation systems, and natural language processing are the core emphasis of deep convolutional neural networks.

Layering is what gives DCNNs their power. A DCNN processes the image's Red, Green, and Blue components simultaneously by using a three-dimensional neural network. When compared to feed forward neural networks, this significantly lowers the amount of artificial neurons needed to analyse an image. Using photos as an input, deep convolutional neural networks build a classifier. The network uses something other than matrix multiplication: a unique mathematical process known as a "convolution."

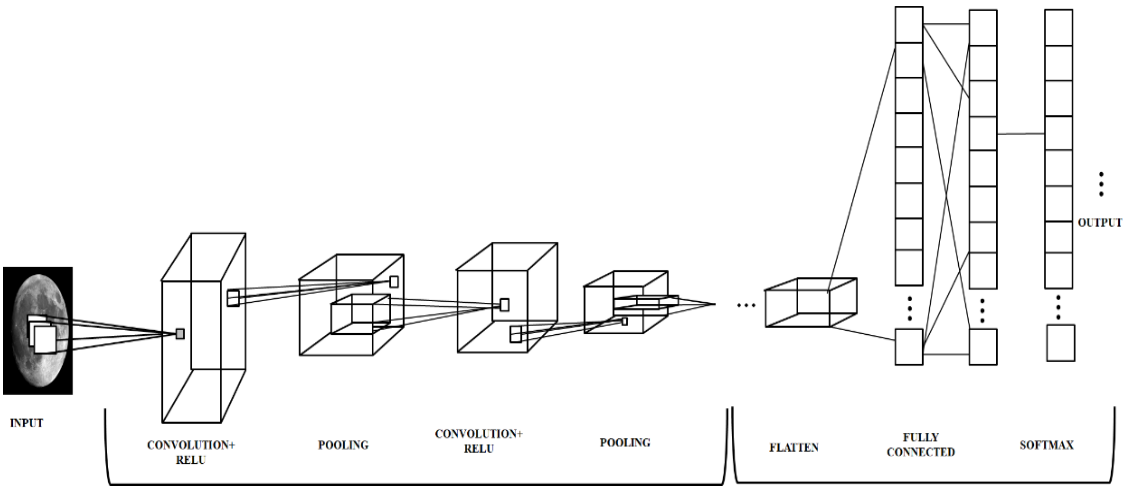

Figure 2: *Diagram of the DCNN architecture*

2.3.1 Convolutional Layer

Applies a convolution filter to the picture in order to identify its characteristics. The different characteristics from the input photos are initially extracted using this layer. This layer performs the convolutional mathematical process between an input picture and a filter with a specified MxM size. The dot product between the filter and the portions of the input picture with regard to the filter's size (MxM) is calculated by swiping the filter over the image.

2.3.2 ReLU Activation Layer

A nonlinear activation layer, such as a Rectified Linear Unit (ReLu), is applied to the convolution maps, replacing the filtered pictures' negative integers with zeros.

a) Pooling Layer

A Pooling Layer usually comes after a Convolutional Layer. This layer's main goal is to save computational expenses by shrinking the convolved feature map. Reducing the connections between layers and working on each feature map separately allows for this. Diverse pooling operations exist, depending on the approach taken. The image is gradually shrunk by the

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pooling layers, which preserve just the most crucial details. For instance, in each group of four pixels, either the maximum-valued pixel (max pooling) or merely the average pixel (average pooling) is kept. By lowering the amount of computations and parameters in the network, pooling layers aid in the management of overfitting. The biggest piece from the feature map is used in max pooling. The average of the components in an Image segment of a certain size is determined by average pooling. Sum Pooling computes the total sum of the components in the designated section. Typically, the Pooling Layer acts as a link between the FC Layer and the Convolutional Layer. At the conclusion of the network is a conventional multi-layer perceptron or "fully connected" neural network, which is the result of several repetitions of convolution and pooling layers (in certain deep convolutional neural network topologies, this may happen thousands of times).

b) Fully Connected Layer

Activation and pooling layers sit in between many fully linked layers seen in various CNN systems. The neurons are connected between two separate layers by the Fully Connected (FC) layer, which also includes the weights and biases. These layers make up the final few levels of the CNN structure and are often positioned before the output layer. An input vector comprising the image's flattened pixels—which have been filtered, adjusted, and reduced by convolution and pooling layers—is sent to fully linked layers. The outputs of the fully connected layers are subjected to the softmax function in the end, which yields the likelihood of the picture belonging to a particular class, such as diabetes or not. This involves flattening and feeding the input picture from the earlier levels to the FC layer. After that, the flattened vector proceeds through a few additional FC levels, which are often where mathematical calculations are performed. At this point, the process of categorization starts.

C) Dropout

Overfitting in the training dataset is typically a result of connecting every feature to the FC layer. When a model performs so well on training data that it adversely affects the model's performance on fresh data, this is known as overfitting. In order to solve this issue, a dropout layer is used, in which a small number of neurons are removed from the neural network during training, reducing the size of the final model. Thirty percent of the nodes in the neural network are randomly removed after a dropout of 0.3.

d) Activation Functions

Lastly, the activation function is among the CNN model's most crucial elements. They are employed in the learning and approximation of complicated and continuous relationships between network variable types. Put simply, at the end of the network, it determines which model information should shoot ahead and which ones shouldn't. It gives the network more nonlinearity. Numerous widely-utilized activation functions exist, including the Sigmoid, ReLU, Softmax, and tanH functions. Every one of these features has a distinct application.

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Softmax is utilised for multi-class classification, and sigmoid and softmax functions are recommended for a CNN model used for binary classification. Votes are generated from the high-level filtered pictures by the neural network's fully connected layers. The weights, or link strengths, between each value and each category are the results of these votes. A freshly fed picture to the CNN travels up through the tiers until it reaches the final fully linked layer. After then, a vote is taken. The response that receives the most votes is selected as the input's category.

3 Result and Discussion

The suggested strategy is implemented in Python and the outline of the experimental design and findings in this part are as follows. The dataset and assessment metrics are introduced and to improve recognition performance on the dataset are described and the testing outcomes are shown below.

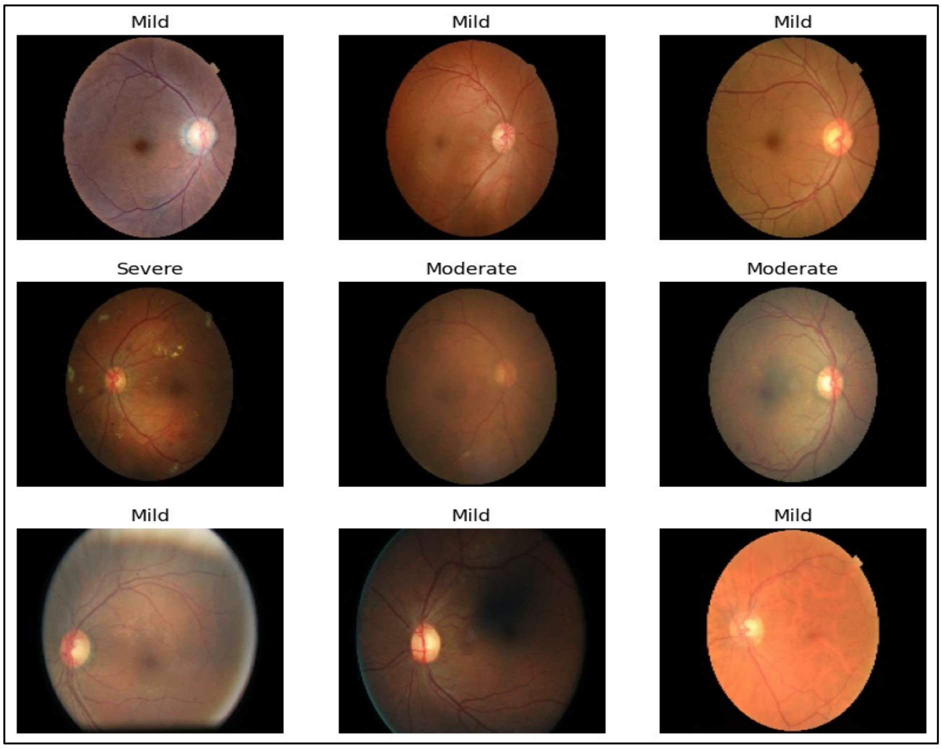

Figure 3: *Input Image Dataset*

The eyes' input picture collection is shown in Figure 3. Because of its great resolution, the MR image is provided as an input. The input picture is also in grayscale. Images of both normal and pathological diseases are included in the database. Only one of the pictures is used as the input.

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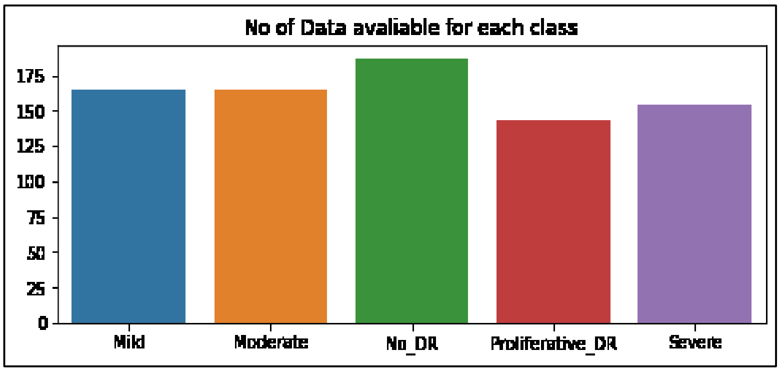

Figure 4: *Data distributions for each class*

The data distribution for the normal data and the four forms of diabetic retinopathy is shown in Figure 4. For a particular kind of retinopathy, each of these datasets surpasses the 150 datasets that are currently accessible.

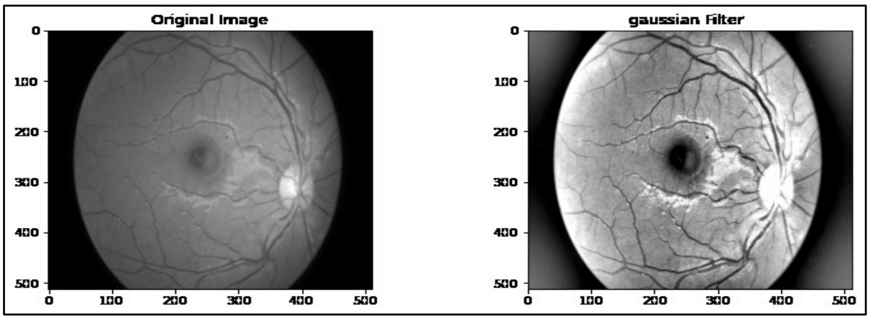

Figure 5: Preprocessed Image for Gaussian filter

Figure 5 shows a filtered, pre-processed picture. Before beginning the real process, each image needs to be minimally pre-processed in order to be suitable for additional processing. Gaussian filter is used to handle this pre-processed picture. In addition to improving the image, it is done to eliminate noise. It is a procedure used to improve an image's accuracy and interpretability.

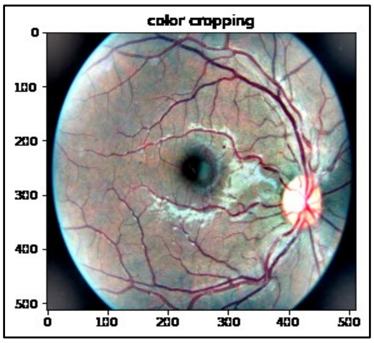

Figure 6: *Color Cropped Image*

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Illustrations of the colour cropped image are presented in Figure 6. The technique of eliminating undesired areas of a picture, often those around the borders, in order to draw attention to a particular topic or enhance its composition is known as "colour cropping."

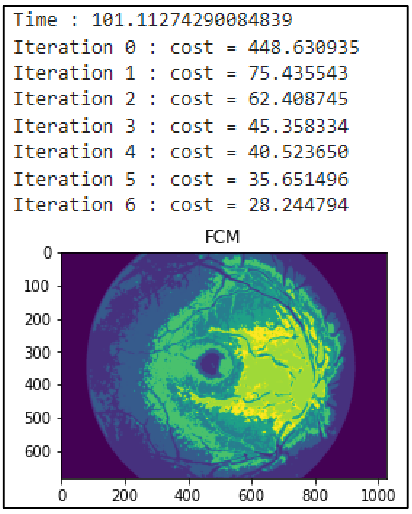

Figure 7: *Segmented Image*

Figure 7 shows a segmented view of the eyes. The diagnosis of fundus disorders greatly depends on retinal segmentation. Retinal scans have therefore been routinely employed to identify systemic vascular disease early on. Accurate vascular segmentation is necessary to aid in the detection of systemic illnesses. Segmentation is the process of breaking a digital picture up into many parts. Fuzzy C-means (FCM) is used to aid with the segmenting process.

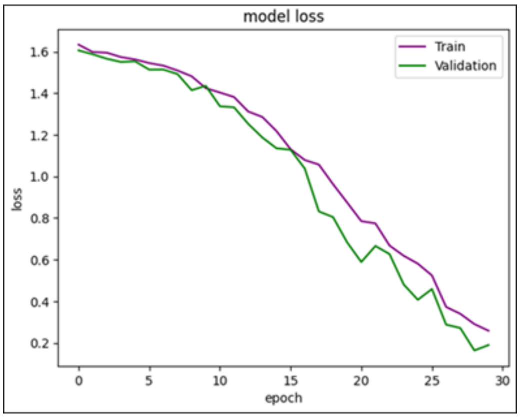

Figure 8: *Model Loss*

The number of categories a model successfully predicts divided by the total number of predictions produced is the definition of model accuracy. It is one method of evaluating a model's performance, but it is by no means the only one. Presents of the model correctness are

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shown in Figure 8. A purple colour line represents train loss, and a green colour line indicates validation loss.

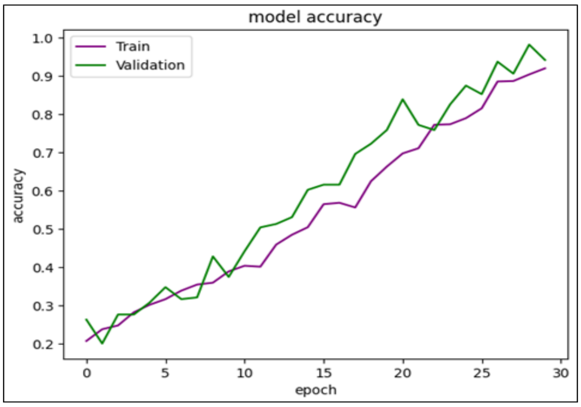

Figure 9: *Model Accuracy*

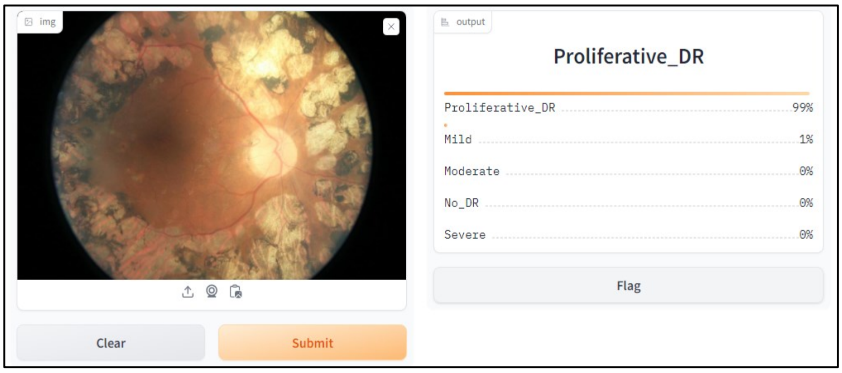

Figure 10: *Proliferative DR*

Based on five different types of datasets to determine retinopathy classes, Figure 10 depicts retinopathy. Proliferative DR predictions are successful in 99.9% of cases.

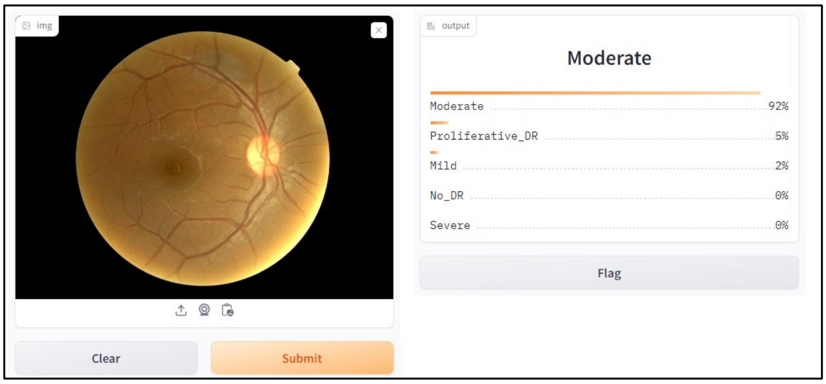

Figure 11: *Moderate*

ISSN (Online): 2583-7052

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In order to detect the disorders, Figure 11 creates diabetic retinopathy utilising five distinct datasets. Success means that 92% of moderate cases, 5% of proliferative cases, and 2% of mild cases are anticipated.

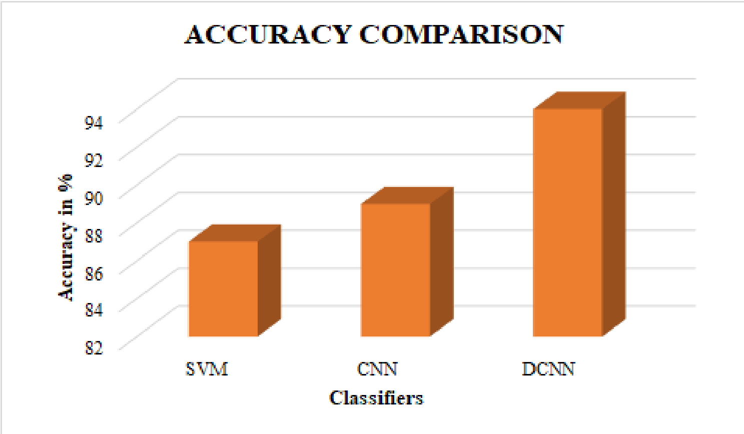

Figure 12: *Accuracy Comparison*

Figure 12 shows the accuracy comparison of various classifiers in which it shows DCNN shows highest accuracy of 94.7%.

4 Conclusion

Elevated blood sugar levels harm the retina, the back of the eye, resulting in diabetic retinopathy. Based on DCNN, this study offers an accurate prediction of the forms of diabetic retinopathy. The investigations in this paper have been analysed from the perspectives of the input image applied, the picture pre-processing methods utilised and the colour cropped method employed, in accordance with the inclusion criteria and quality evaluation. The segmentation technique and DCNN classification that will be utilised to precisely identify diabetic retinopathy are included in this work and it shows 94.7%. It was successfully determined that the illness type is impacted by this methods. The right course of action for treatment and care is determined in part by this information. In cases when the patient has a history of diabetic retinopathy and has received routine tests, the result offers an evaluation of the disease's course. It supports therapy efficacy monitoring and provides information for next managerial choices. This study offers a prognostic evaluation based on the severity of diabetic retinopathy and the patient's reaction to therapy. It also aids in establishing expectations for possible results and the significance of continuous management.

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