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A SYSTEMATIC APPROACH FOR ANALYSIS OF RETINAL IMAGES FOR DIABETIC RETINOPATHY DETECTION

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Abstract: Diabetic retinopathy (DR) is a condition that occurs as a result of damage to the blood vessels of the retina in people who have diabetes. DR can be developed if one has Type - 1 or Type - 2 diabetes and a long history of uncontrolled high blood sugar levels. There are different forms of diabetic retinopathy such as non-proliferative Diabetic Retinopathy (NPDR), proliferative Diabetic Retinopathy (PDR) and Macular Edema (ME) [1] [2]. In case of NPDR blood vessels in the retina become week which results in Microaneurysms (MA), Haemorrhages (HA). While in case of PDR, areas of retina become oxygen deprived which leads to abnormal growth of blood vessels. Macular Edema represents the swelling of macula. Several parameters are associated with the growth of Diabetic Retinopathy [3] [4], such as, metabolism control density and genetic-constraint. During the primary phase, the arteries in retina begin to leak and minute haemorrhages are created [5] [6]. The vessels, which leaks from lipoproteins lead to blurred vision. Another crisis is the growth of weaker blood vessels that burst and leaks blood in eyes, and therefore the retina will not be able to project images to brain that paves the way for blindness. As DR [7] [8] is a chief cause of visual loss among individuals suffering from diabetes [9], it is necessary to diagnose them frequently so as to spot the symptoms of DR at the earliest [10] [11] [12].

Nowadays, Computer Aided Diagnostic system (CAD) [13] [14] is introduced for diagnosing the issues in eye diseases. "CAD is an interdisciplinary technology combining elements of artificial intelligence and computer vision with radiological and pathology image processing". Moreover, CAD systems [15] have been widely exploited due to their capability to aid clinicians in making proper decisions with reduced inconsistency. In particular, "radionics-driven CAD" [14] [15] has turned to be a prevalent area of research subject. Nevertheless, traditional radiomic sequences include hand-crafted, generic features that may limit the recognition of certain disease behaviours [14] [15].

***Index Terms* – Diabetic Retinopathy, Retinal Images, Fundus Images.**

I. INTRODUCTION

Diabetic retinopathy has become a common disease around the world. Although diabetes affects the eye in many ways (for example, the high risk of cataracts), diabetic retinopathy is the most common and most serious ocular complication. Early detection is the key to slowing the progression of the disease, thus preventing blindness. Discovering the disease in its early stages may reduce the chances of blindness. Computing technologies and machine learning tools can be used to assist physicians in diagnosing and predicting the disease so they can provide the necessary treatment and prevent the impact.

Analysis of retinal images with a high accuracy of diabetic fundus images screening and classification will help in decreasing the workload for healthcare personnel in the process of the early detection of DR. Therefore, it is proposed to utilize the MATLAB approach in its early diagnosis, focusing on segmentation approach in medical images to produce models and methods that can assist physicians in the process of detection of Diabetic Retinopathy.

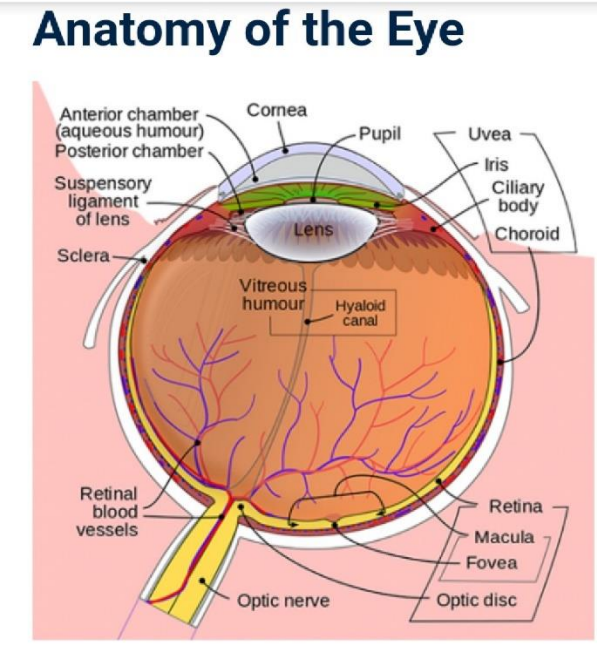

Fig 1. Anatomy of Eye

Fig. 1 shows the details of the anatomy of human eye. It consists of Sclera, Choroid, Retina, Macula and muscle, Iris, Pupil, Cornea, Anterior Chamber (filled with aqueous humor) lens etc.
Light passes through the front of the (cornea) to the eye. The cornea and the lens help to focus the light rays onto the back of the eye (retina). The cells in the retina absorbs and convert the light to electrochemical impulses which are transferred along the optic nerve and then to the brain. The eye has a number of components which include but are not limited to the Cornea, Iris, Pupils etc.
Cornea: - Clear front window of the eye that transmit and focuses light into the eye.
Choroid: - Layer containing blood vessels that lines the back of the eye and is located between the retina (the inner light-sensitive layer) and the Sclera (the outer white eye wall). Ciliary Body: - Structure containing muscle and is located behind the iris, which focuses the lens. Fovea: -The center of the macula which provides the sharp vision.

Iris: - The colored part of the eye which helps the regulate the amount of the light entering the eye. Where there is a bright light, the iris closes the pupil to let in less light. and, where there is low light, the iris opens up the pupil to let in more light.
Lens: - Focuses light rays onto the retina. The lens is transparent, and can be replaced if necessary. Intraocular lenses are used to replace lenses clouded by cataracts.
Macula: - The area in the retina that contains special light-sensitive cells. In the macula these light- sensitive cells allow us to see fine details clearly in the center of our visual field. The deterioration of the macula is a common condition as we get older (Age Related Macular Degeneration or ARMD).
Optic Nerve: - A bundle of more than a million nerve fibers carrying visual message from the retina to the brain. Brain actually controls what you see, since it combines images. The retina sees Images upside down but the brains turns images that we can see much like mirror in a camera.
Glaucoma is one of the most common eye conditions related to optic nerve damage.
Pupil: - The dark center opening in the middle of the iris. The pupil changes the size to adjust for the amount of light available (smaller for bright light and larger for low light). This opening and closing of light into the eye is much like the aperture in most 35mm cameras which lets in more or less light depending upon the conditions.
Retina: - The nerve layer lining the back of the eye. The electrical impulses that are sent through the optic nerve to the brain.
Sclera: - The white outer coat of the eye, surroundings the iris.

Vitreous Humor: - The clear, gelatinous substances filling the central cavity of the eye. Cones: - The photoreceptor nerve cells present in the fovea (that vary center of the macula).

I. RESEARCH METHODOLOGY

The proposed work in this paper article depicts to make certain investigation on history, current status and viable approaches for Diabetic Retinopathy detection. It gives details to examine publicly available datasets in the field of Diabetic Retinopathy detection and their availability. It helps to contribute in identifying key features that paves way for appropriate diagnosis of Diabetic Retinopathy in early stage. Mainly to determine a method for automatic detection of Diabetic Retinopathy. This leads to make a comparison with state-of-the-art methods for proving the betterment of proposed work with respect to different performance measures. methodology section outlines the plan and method that how the study is conducted.

Nowadays, analysis on retinal image exists as one of the challenging area for study. Numerous retinal diseases could be recognized by analyzing the variations taking place in retina. The proposed methodology will be to formulate solutions for the identified problems. Thus proposed methodology involves various phases such as pre-processing, segmentation, feature extraction and classification.

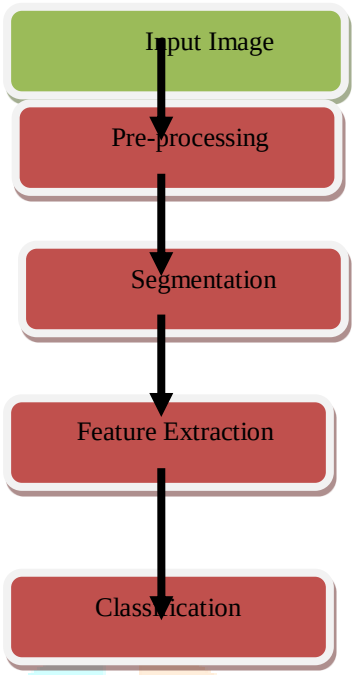

Fig 2 : Implementation Methodology

II. Implementation

The proposed work is implemented on Intel CORE processor i5, 8GB RAM Laptop configuration and operating system is Windows 10. MATLAB R2018b software was used to write the programming code in this we used Image processing, Statistics and Machine Learning toolbox and Deep Learning toolbox. The input images are taken from Kaggle (APTOS 2019 Blindness Detection) Dataset [26] for experimentation. section elaborates the proper statistical/econometric/financial models which are being used to forward the study from data towards inferences. The detail of methodology is given as follows. Training Phase:

In this experimentation, as per proposed block diagram, we have two implementation phase, first training and then testing. In training, train set of images need to be preprocessed as per dimension of deep network used. And then for feature extraction process of train images, we used automated feature extraction based on Inception V3 pre-trained deep convolutional neural network in which it consists of total 316 layers including input, feature, classification and output layer shown in Fig 4 and 5. We have used 'avg_pool' feature layer to extract the features from images. Then after extraction features, we need to train the model using multi kernel SVM based on input and output data, where input is train image feature dataset and output is labels. After successful validation of training model, we saved the trained model.

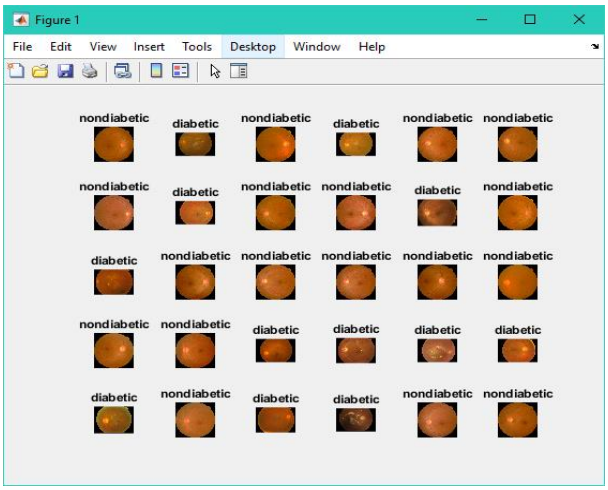

Fig: 3: Sample Images of Chest CT Scan Dataset

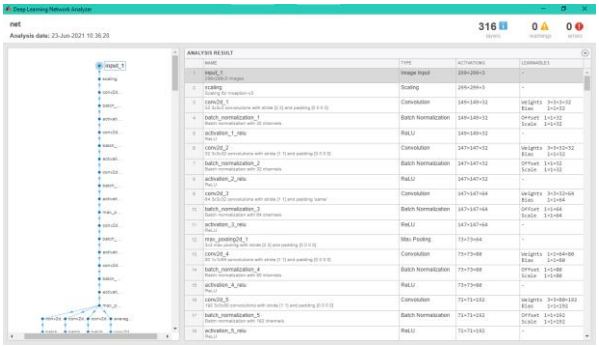

Fig: 4: Initial layers of Inception V3 architecture

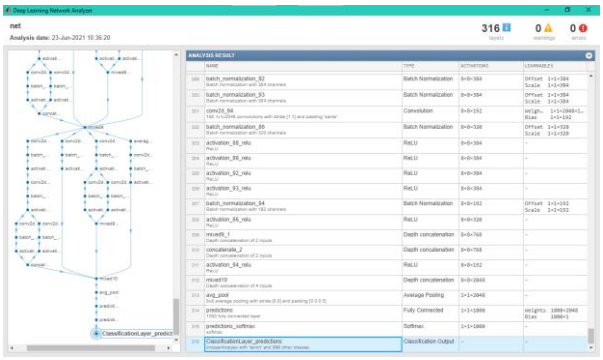

Fig: 5 : Final layers of Inception V3 architecture

Fig 3 showed the samples images of dataset with total 2048 features of whole dataset images having dimension of 70*2048 in Fig 4. Model validation accuracy and total evaluation time required for project to evaluate dataset features is shown in Fig 5 and Fig 6.

```
Command Window

net =

  DAGNetwork with properties:

         Layers: [316×1 nnet.cnn.layer.Layer]
    Connections: [350×2 table]


inputSize =

   299   299     3

Train Dataset Feature Size
  Name                Size                Bytes  Class     Attributes

  featuresTrain      70x2048             573440  single
```

Fig: 6: Feature dimensions of train dataset images

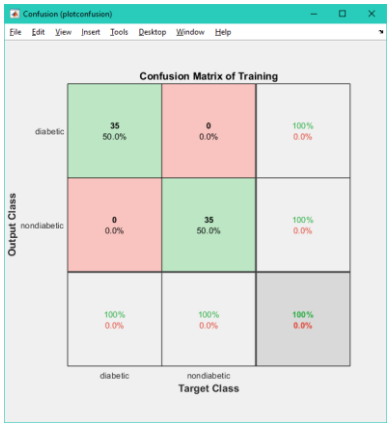

Fig: 7 : confusion matrix of model validation

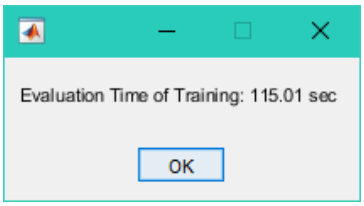

Fig: 8 : Evaluation time required for training of project

Fig 7 gives the confusion matrix of the model validation and Fig 8 shows the evaluation time required for training after providing the image inputs.

III. Testing Phase:

In testing phase, we need apply same procedure as for train images to predict the output whether it is the proper fundus retinal image.

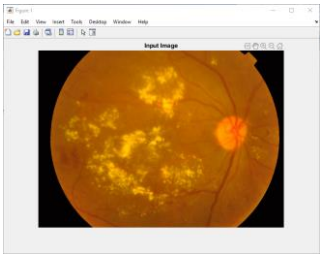

Fig: 9 : Input Test Image – Diabetic

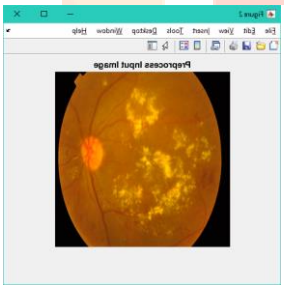

Fig: 10 : Pre-process Input Image

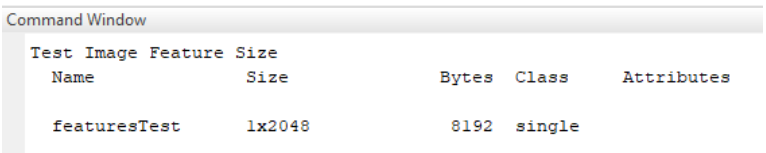

Fig: 11 : Feature dimension of Test Image

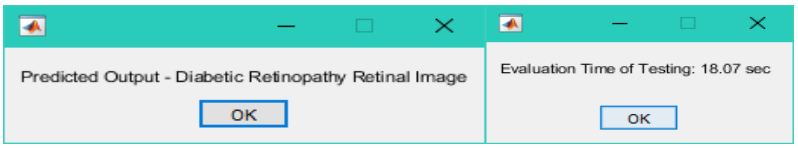

Fig: 12 : a) Predicted Output b) Evaluation time required for testing of image

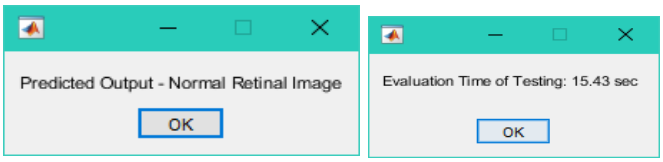

Fig: 13 : a) Predicted Output b) Evaluation time required for testing of image

Subsequent inputs provided give extra results shown in Figures 9 to 13.

IV. RESULTS AND DISCUSSION

A systematic approach using MATLAB is deliberated. After giving the various available retinal images from the available data set, it is concluded that the output of the trained system gives inference whether the input image is prone to diabetic retinopathy or not. This would help the doctor to take an early decision for further line of treatment for the patient.

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