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Diagnosis of Retinal Diseases Using SLO

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ABSTRACT: Examining laser ophthalmoscopes (SLOs) can be utilized for as a part of front of timetable ID of retinal illnesses. With the incident to most recent screening progression, the upside of utilizing SLO is its wide field of perspective, which can picture a broad part of the retina for better finding of the retinal sicknesses. Then again, amidst the imaging procedure, out of date rarities, for occurrence, eyelashes and eyelids are in like way imaged near to the retinal region. This brings a critical test on the most able strategy to deny these old rarities. In this paper, we propose a novel way to deal with oversee ordinarily remove out true blue retinal zone from a SLO picture in context of picture dealing with and machine learning approaches. To decrease the multifaceted method for picture dealing with errands and give a strong primitive picture arrangement, we have gathered pixels into various ranges considering the provincial size and conservativeness, called super pixels. The structure then procedures picture based parts reflecting textural and crucial data and solicitations between retinal space and old-fashioned rarities. Performance of this proposed technique is compared with GLCM and texture feature in terms of MSE and classification accuracy. It also gives better accuracy and reduced MSE of 98.0% and 0.585 respectively. Thus, the resultant SFTA technique performs more accurately than the previous works.

KEYWORDS: Feature selection, retinal artefacts extraction, retinal image analysis, scanning laser ophthalmoscope (SLO) SFTA.

I. INTRODUCTION

Early area and treatment of retinal eye diseases is fundamental to keep up a Strategic separation from preventable vision setback. Expectedly, retinal ailment recognizing verification frameworks rely on upon manual discernments. Optometrists and ophthalmologists routinely rely on upon picture operations, for instance, change of separation and zooming to interpret these photos and dissect results in perspective of their own experience and zone data. These symptomatic techniques are dull. Robotized examination of retinal pictures can lessen the time, which clinicians need to look at the photos, which can expect that more patients will be screened besides, all the more consistent investigations can be given in a period viable manner [1]. The 2-D retinal scopes gained from imaging instruments [e.g., fundus camera, checking laser ophthalmoscope (SLO)] may contain structures other than the retinal zone; all around saw as antiquated rarities. Denial of ancient pieces is indispensable as preprocessing endeavor before robotized area of components of retinal diseases. In a retinal yield, coincidental dissents, for instance, the eyelashes, eyelids, and dust on optical surfaces may appear to be splendid and in center hobby. Thusly, customized division of these old rarities from an imaged retina is not an irrelevant task. The inspiration driving performing this study is to develop a technique that can restrict relics from retinal compasses with a specific end goal to upgrade customized acknowledgment of disease parts from the retinal yields. To the best of our understanding, there is no present business identified with partition between the veritable retinal zone and the relics for retinal area acknowledgment in a SLO picture. The SLO created by Optos [2] produces photos of the retina with a width of up to 200° (measured from the point of convergence of the eye). This contemplates to 45°–60° achievable in a lone fundus photograph. Tests of retinal imaging using fundus camera and SLO are showed up in Fig. 1. In light of the wide field of viewpoint (FOV) of SLO pictures, structures, for instance, eyelashes and eyelids are moreover imaged nearby the retina. In case these structures are evacuated, this will not simply energize the convincing examination of retinal zone, moreover enable to enlist multi view pictures into a montage, achieving an absolutely recognizable retina for infection investigation. In this study, we have built up a novel structure for the extraction of retinal region in SLO pictures. The three essential steps for building our framework. For isolating between the retinal domain and the relics, we have chosen particular picture based

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 7, July 2016

segments which reflect grayscale, textural, and fundamental information at various resolutions. By then, we have picked the parts among the considerable rundown of capacities, which are applicable to the gathering. The segment determination process upgrades the classifier execution to the extent computational time. Finally, we have built up the classifier for isolating between the retinal zone and the antiquated rarities. Our model has finished typical course of action accuracy of 92% on the dataset having sound.

II. RELATED WORK

Our writing review is started with the techniques for location and division of eyelids and eyelashes connected on pictures of the front of the eye, which contains the student, eyelids, and eyelashes. On such a picture, the eyelashes are more often than not as lines or bundle of lines assembled together. In this way, the initial step of identifying them was the use of edge recognition systems, for example, Sobel, Prewitt, Canny, Hough Transform [3], and Wavelet change [4]. The eyelashes on the iris were then evacuated by applying nonlinear separating on the suspected eyelash regions [5]. Subsequent to eyelashes can be in either divisible structure or as different eyelashes gathered together, Gaussian channel and Variance channel were connected so as to recognize among both types of eyelashes [6]. The test demonstrated that detachable types of eyelashes were undoubtedly distinguished by applying Gaussian channel, though Variance channels are more ideal for different eyelash division [7].

At first, the eyelash hopefuls were limited utilizing dynamic shape demonstrating, and after that, eight-directional channel bank was connected on the conceivable eyelash applicants. Kang and Park [8] utilized center score as a part of request to shift the measure of convolution portions for eyelash recognition. The size variety of the convolution parts likewise separated between detachable eyelashes and numerous eyelashes. Min and Park [9] decided the components in view of force and neighborhood standard variety so as to decide eyelashes. They were edge utilizing Otsu's strategy, which is a programmed limit determination technique taking into account specific suspicions about force dissemination. These techniques have been connected on CASIA database [10], which is an online database of Iris pictures. In an picture acquired from SLO, the eyelashes show as either dull or brilliant locale contrasted with retinal range contingent on how laser pillar is engaged as it passes the eyelashes. The eyelids show as reflectance locale with more noteworthy reflectance reaction contrasted with retinal range. Along these lines, we have to discover elements, which can separate among genuine retinal zone and the ancient rarities in SLO retinal sweeps.

After visual perception in Fig. 1(b), the elements mirroring the textural and basic distinction could have been the recommended decision. These components have been figured for various locales in fundus pictures, generally for quality examination. The portrayal of retinal pictures were performed as far as picture elements, for example, force, skewness, textural investigation, histogram examination, sharpness, and so forth., [1], [11], [12]. Dias et al. [13] decided four unique classifiers utilizing four sorts of elements. They were dissected for the retinal range including shading, center, differentiation, and enlightenment. The yield of these classifiers was connected for quality arrangement. For grouping, the classifiers, for example, fractional minimum square (PLS) [14] and bolster vector machines (SVMs) [15] were utilized. PLS chooses the most applicable elements required for grouping. Aside from ascertaining picture highlights for entire picture, network examination containing little fixes of the picture has likewise been proposed for diminishing computational many-sided quality [11]. For deciding picture quality, the components of locale of enthusiasm of anatomical structures, for example, optic nerve head (ONH) and Fovea have additionally been dissected [16].

The components included basic similitude list, zone, and visual descriptor and so forth. A percentage of the aforementioned systems propose the utilization of lattice examination, which can be a time successful technique to create elements of specific area as opposed to every pixel. Yet, lattice examination won't not be an exact approach to speak to sporadic districts in the picture. In this manner, we chose the utilization of superpixels [17]–[20], which amass pixels into various locales relying on their territorial size and smallness. Our approach depends on breaking down the SLO picture based components, which are computed for a little district in the retinal picture called superpixels. The determination of highlight vector for each superpixel is computationally productive when contrasted with highlight vector determination for every pixel. The superpixels from the pictures in the preparation set are doled out the class of either retinal territory or relics relying on the lion's share of pixels in the superpixel having a place with the specific class. The characterization is performed in the wake of positioning and determination of components as far as viability in order. The subtle elements of the strategies are talked about in the accompanying are

International Journal of Innovative Research in Science, Engineering and Technology

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Vol. 5, Issue 7, July 2016

III. MOTIVATIONS

Photos of poor quality might lead to incorrect automatic diagnosis of a disease and the grading of its severity. Thus, an expert must first visually classify the images as gradable or upgradable. A retinal image is deemed upgradable if it is impossible to make a reliable clinical judgment regarding the presence or the type of disease. Figure 1.1 shows examples of one gradable and three upgradable retinal images. Visual analysis of large databases of retinal images is a time consuming task that can be spread among a large number of experts. However, this may lead to inter-variability between results in the quality assessment or in the diagnosis provided by different experts. Automatic analysis of retinal images is thus a possible solution for the shortage of human experts and for reproducible clinical assessment. Moreover, in order to better understand the cause and progress of diseases, one may need to analyze many images over a long period of time. Automated retinal images quality analysis can reduce the need for human intervention and provide better conditions for more studies, hence increasing the functionality of retinal disease diagnosis.

IV. AIM AND OBJECTIVES

Main aim of proposed system is to implement retinal image quality assessment algorithm which relies on the measure of generic image features, namely colour, focus, contrast and illumination computed using specific algorithms. To achieves state-of-the-art localization performance in both accuracy and speed, and brings a significant improvement in iris recognition accuracy.

The main objective of this thesis is to propose an automatic image quality assessment approach to classify retinal images as gradable or upgradable. This general objective is divided into six specific objectives that together achieve the overall goal of the project.

i. Develop an algorithm to identify a region of interest for further analysis. Under this objective, the project will result in an algorithm to remove irrelevant image information in color retinal images that consist of a circular region (foreground) on a black background.

ii. Propose an approach to measure generic features containing textural, local sharpness, edge ratio and color histogram features. These extracted features are used for the classification of the images as gradable or upgradable.

iii. Propose a feature selection technique to reduce the dimensionality of the features vector by selecting only a subset of measured features. The goal of feature selection is to improve the effectiveness and efficiency of the classification.

iv. Construct an algorithm capable of classifying images as gradable or upgradable, according to measurements performed in the previous stages.

v. Evaluate the sensitivity and specificity of the algorithm based on experimental (visual) observations of eye experts.

vi. Evaluate the proposed method on a region including the main anatomical structures. Since experts commonly consider the macula and optic disc regions as the most useful portions of retinal images, we investigated the difference between a local and a global assessment approaches.

V. PROPOSED MECHANISM AND ARCHITECTURE

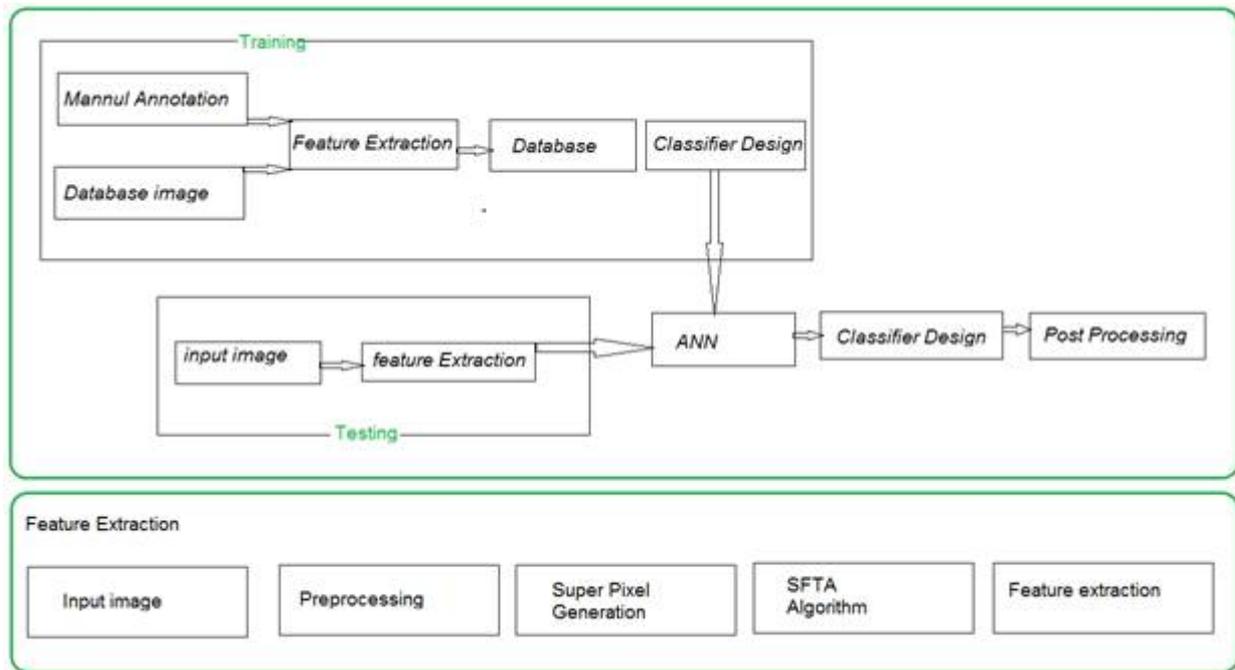


Fig. 1. Block diagram of retina detector framework

The piece outline of the retina indicator system is appeared in Fig. 2. The structure has been partitioned into three stages, in particular preparing stage, testing and assessment stage, and sending stage. The preparation stage is worried with working of arrangement model taking into account preparing pictures and the explanations mirroring the limit around retinal range. In the testing and assessment arranges, the programmed comments are performed on the "test set" of pictures and the classifier execution is assessed against the manual explanations for the determination of precision. At long last, the arrangement stage performs the programmed extraction of retinal region. The subtasks for preparing, testing, and arrangement stages are quickly portrayed as takes after:

Image Data Integration: It involves the integration of image data with their manual annotations around true retinal area. **Image Preprocessing:** Images are then preprocessed in order to bring the intensity values of each image into a particular range. **Generation of Superpixels:** The training images after preprocessing are represented by small regions called superpixels. The generation of the feature vector for each superpixel makes the process computationally efficient as compared to feature vector generation for each pixel. **Feature Generation:** We generate image-based features which are used to distinguish between the retinal area and the artefacts. The image-based features reflect textural, grayscale, or regional information and they were calculated for each superpixel of the image present in the training set. In testing stage, only those features will be generated which are selected by feature selection process. **Feature Selection:** Due to a large number of features, the feature array needs to be reduced before classifier construction. This involves features selection of the most significant features for classification. **Classifier Construction:** In conjunction with manual annotations, the selected features are then used to construct the binary classifier. The result of such a classifier is the superpixel representing either the "true retinal area" or the "artefacts." **Image Post processing:** Image post processing is performed by morphological filtering so as to determine the retinal area boundary using superpixels classified by the classification model. The elements of our detection framework are discussed as follows.

A. Image Preprocessing

Images were normalized by applying a Gamma (γ) adjustment to bring the mean image intensity to a target value. γ was calculated .

B. Generation of Superpixels

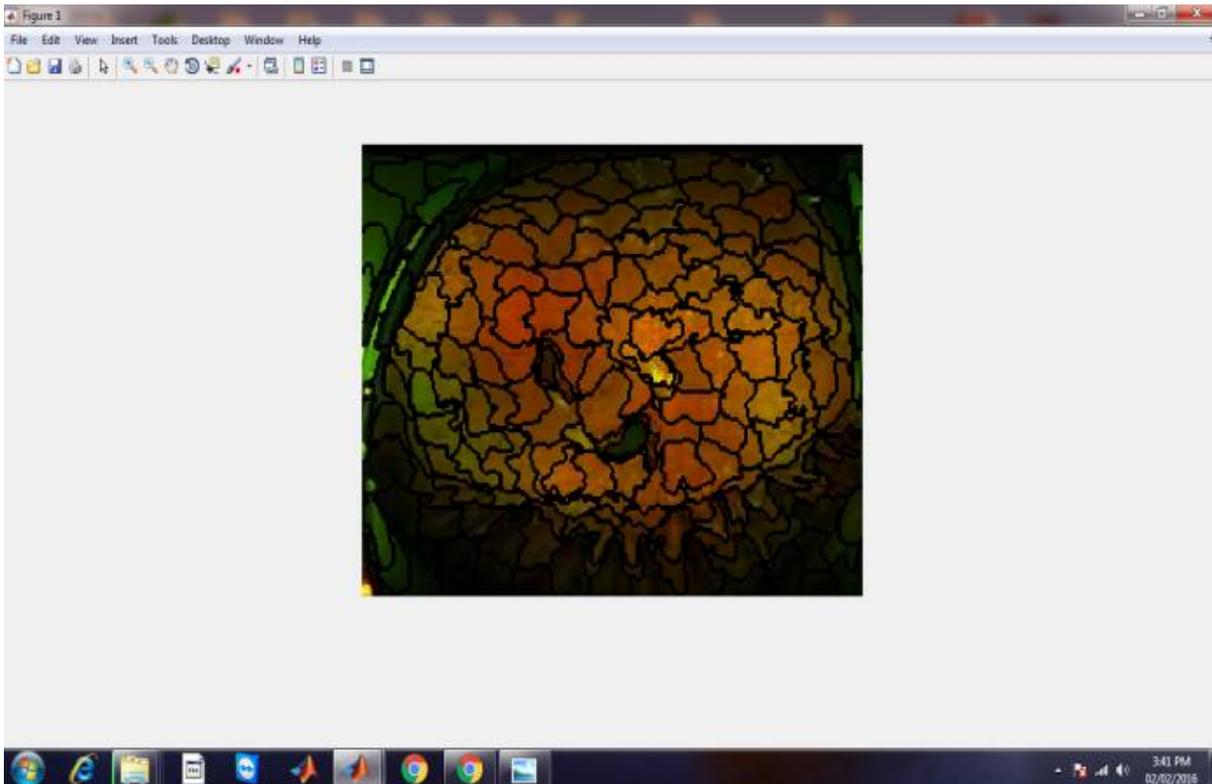


Fig No 02 Generation of Superpixels

The superpixel calculation bunches pixels into various districts, which can be utilized to figure picture highlights while lessening the many-sided quality of consequent picture preparing errands. Superpixels catch picture excess and give a helpful primitive picture design. Similarly as fundus retinal pictures are concerned, the superpixels have been created for examining anatomical structures [21] and retinal discharge identification [22]. For retinal drain location, the superpixels were created utilizing watershed approach however the quantity of superpixels produced for our situation should be controlled. The watershed approach now and then produces number of superpixels of the antiques more than fancied. The superpixel era technique utilized as a part of our retina finder system is basic direct iterative bunching [17], which was appeared to be productive regarding computational time, as well as far as area minimization and adherence. The calculation is introduced by characterizing number of superpixels to be produced. The worth was set to 5000 as a tradeoff between computational dependability and expectation exactness.

Feature Generation

After the generation of superpixels, the next step is to determine their features. We intend to differentiate between the retinal area and artefacts using textural, grayscale gradient, and regional based features. Textural and gradient based features are calculated from red and green channels on different Gaussian blurring scales, also known as smoothing scales [23]. In SLO images, the blue channel is set to zero; therefore, no feature was calculated for the blue channel.

International Journal of Innovative Research in Science, Engineering and Technology

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Vol. 5, Issue 7, July 2016

VI. DIFFERENCE BETWEEN GLCM AND SFTA

1. GRAY-LEVEL CO-OCCURRENCE MATRIX (GLCM)

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. (The texture filter functions, described in [Texture Analysis](#) cannot provide information about shape, i.e., the spatial relationships of pixels in an image.) After you create the GLCMs, you can derive several statistics from them using the [graycoprops](#) function. These statistics provide information about the texture of an image. The following table lists the statistics.

2. SFTA (SEGMENTATION-BASED FRACTAL TEXTURE ANALYSIS)

Extract features from an image using the SFTA (Segmentation-based Fractal Texture Analysis) algorithm. To extract features, use the `sfta(I, nt)` function, where `I` corresponds to the input grayscale image and `nt` is a parameter that defines the size of the feature vector. The features are returned as a $1 \times (6 \times nt - 3)$ vector. It represents a novel feature extraction technique for an automatic classification images. Wavelet based SFTA Feature extraction technique (WSFTA) consists of two steps: (i) Initially the input image is decomposed into different frequency sub band images using 2-D Discrete Wavelet Transform, (ii) the texture features are extracted from the decomposed Low frequency image using SFTA (Segmentation based Fractal Texture Analysis). Two layered feed forward neural network is used for the classification of images into normal or abnormal stages. Performance of this proposed technique is compared with GLCM and texture feature in terms of MSE and classification accuracy. It also gives better accuracy and reduced MSE of 98.0% and 0.585 respectively. Thus, the resultant WSFTA technique performs more accurately than the previous works.

VII. PERFORMANCE CURVE & GRAF OF GLCM & SFTA

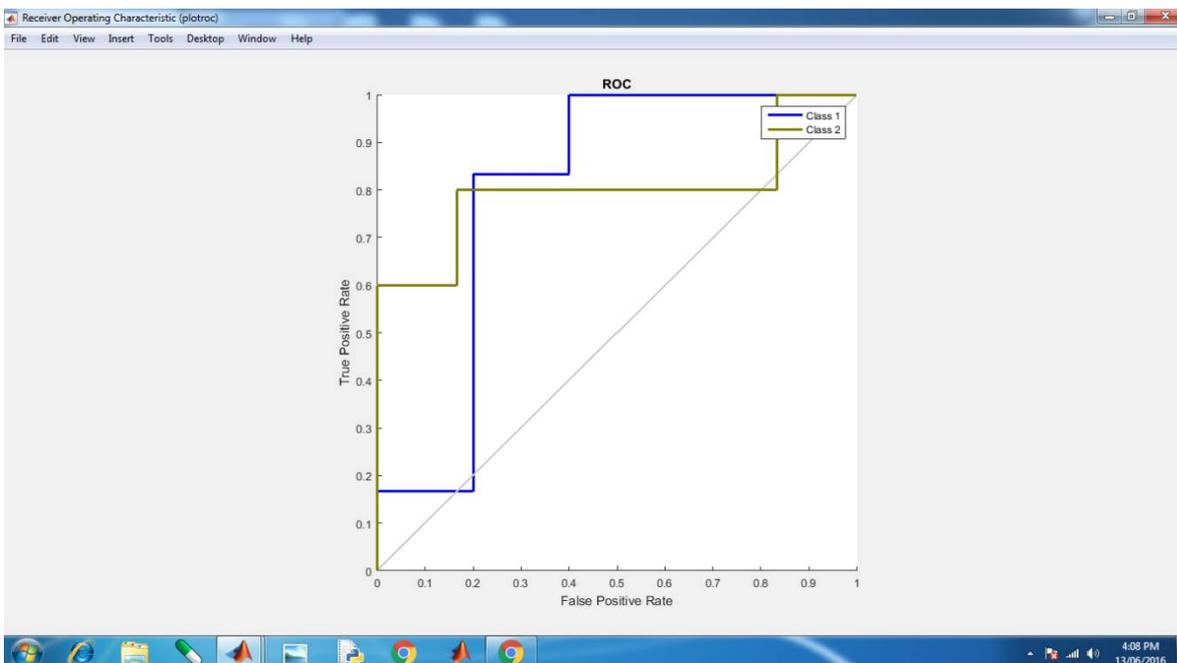


Fig No03 True and False Positive Rate

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 7, July 2016

OUT PUT SCREEN-

Pre-processing the retinal image includes cropping masking and removal of noise from the original image. The result for masking a retinal image i.e. sharpening the original image. Superpixel image is also shown below.

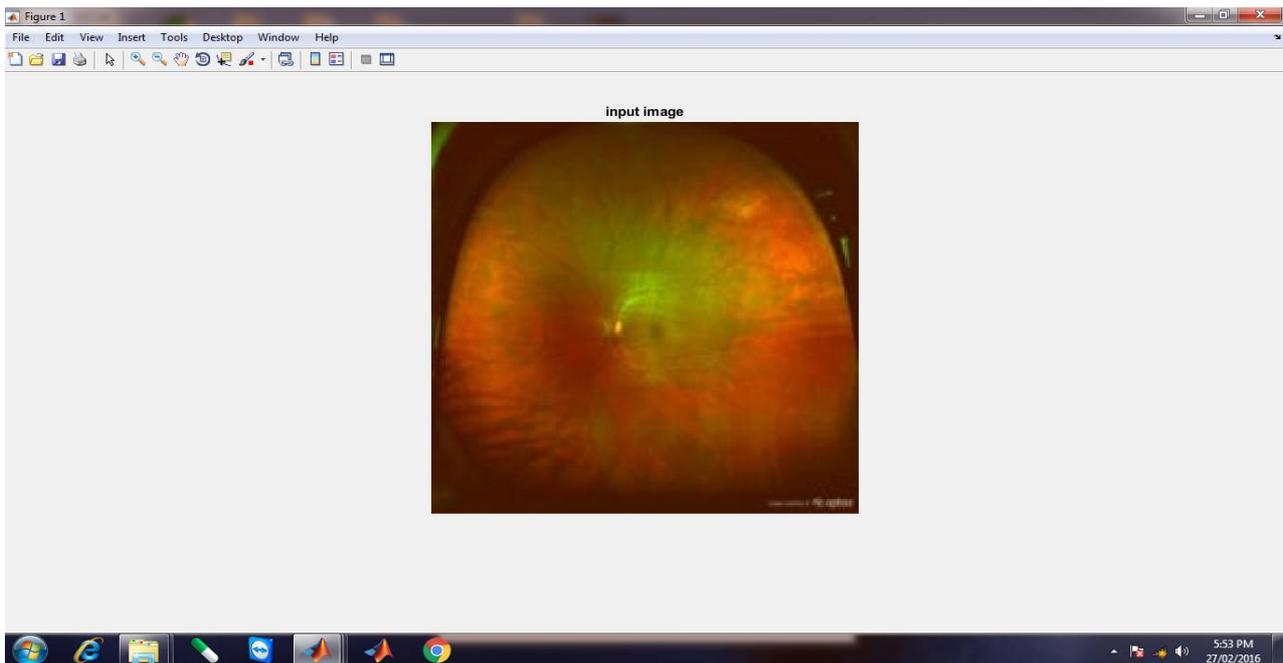


Fig 04 Input

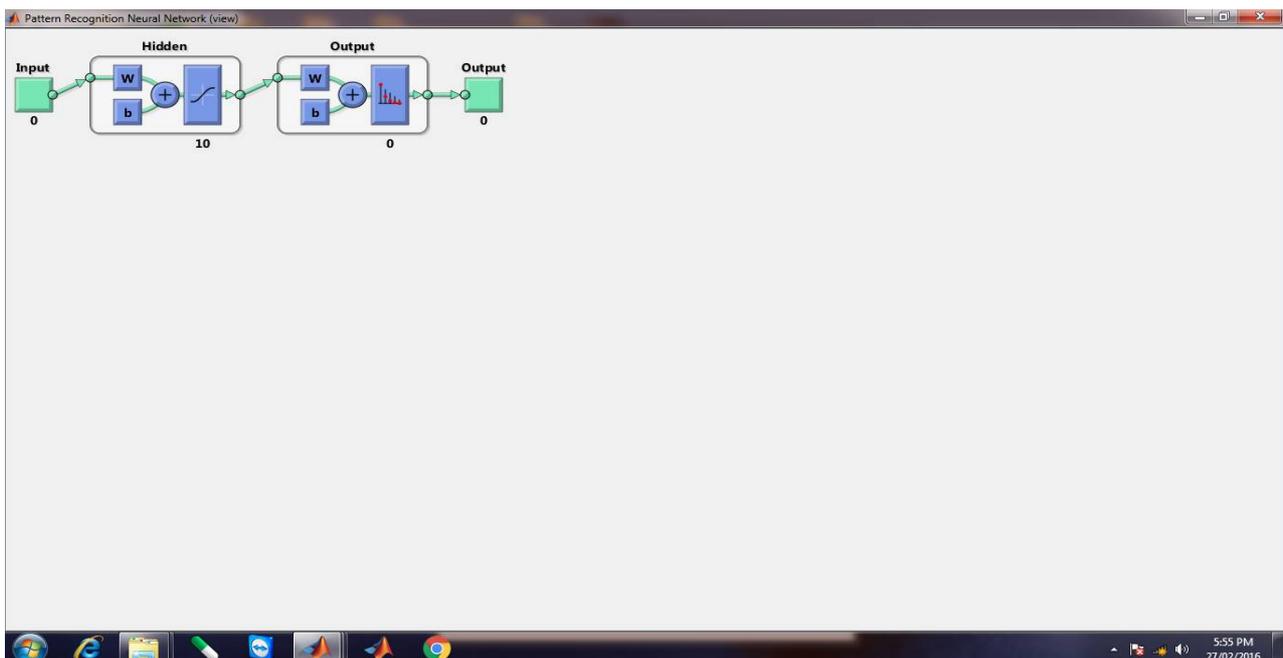


Fig 05 ANN

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 7, July 2016

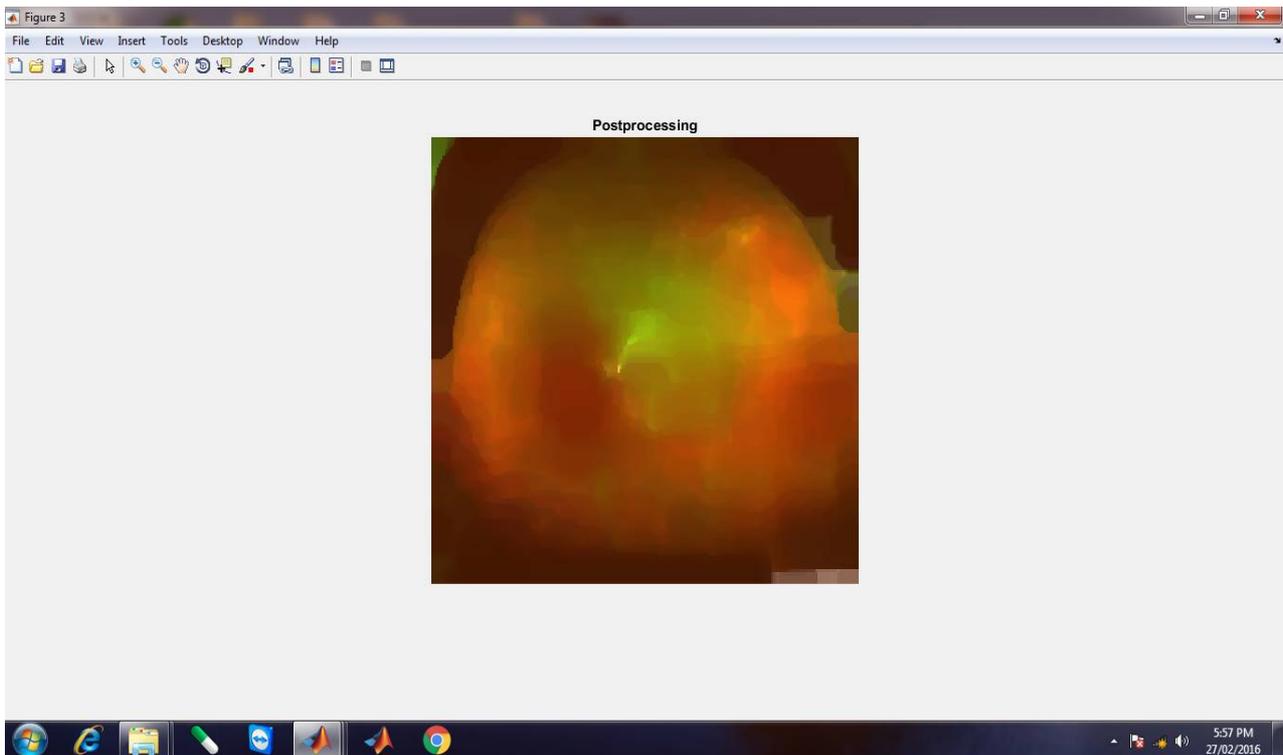


Fig 06 Post Processing



Fig 07 True Retinal Area

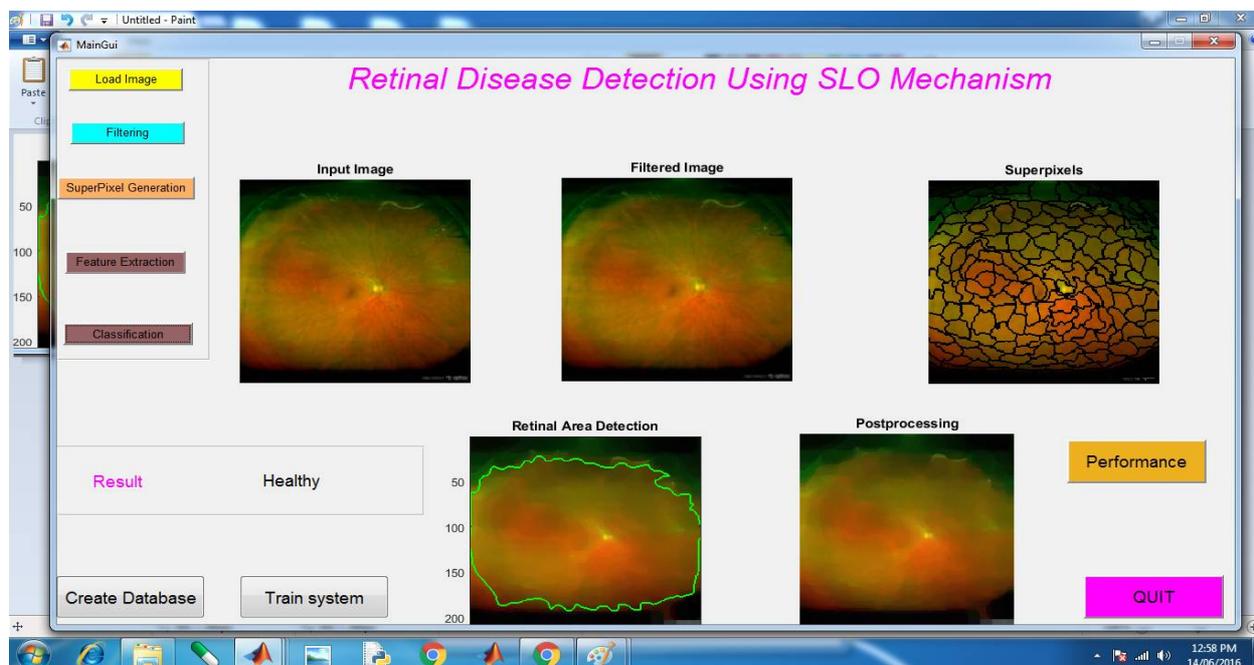


Fig 08 Final Output

VIII. FUTURE WORK

Later on work alongside shading and center appraisal of retinal picture difference and light evaluation must be performed independently. Notwithstanding it each one of those quality markers are consolidated together and grouped to evaluate the picture quality. Alongside this work execution of the classifier is assessed by figuring affectability and specificity. As future work, the primary perspective to take after is to test the proposed strategy utilizing bigger information set as a part of request to assess the execution of the technique all the more precisely. The second viewpoint would be to build up an additional calculation for programmed determination of the area of enthusiasm rather than a self-loader technique.

IX. CONCLUSION

Perceiving bona fide retinal domain from antiquated rarities in SLO pictures is a trying errand, which is in like manner the essential basic step toward PC upheld sickness determination. In this study, we have proposed a novel framework for modified disclosure of authentic retinal zone in SLO pictures. We have used super pixels to address different unusual regions minimally and reduce the handling cost. Highlight decision enables the most basic components to be picked and, hence, diminishes handling cost also. A classifier has been built considering picked components to particular out the retina zone. It has been stood out from other two classifiers and was flawless while saving the computational time. The trial appraisal result shows that our proposed framework can perform a precision of 94% in division of the real retinal zone from a SLO picture. SFTA gives better performance than other techniques with minimum time .

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International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 7, July 2016

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