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DETECTING AND CLASSIFYING DIABETIC RETINOPATHY IN FUNDUS RETINA IMAGES USING ARTIFICIAL NEURAL NETWORKS-BASED FIREFLY CLUSTERING ALGORITHM

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ABSTRACT

Today, image-processing techniques are widely used in fields such as engineering and medical science. This paper focuses on medical imaging, particularly that of retinal images. Diabetic retinopathy has affected many people, and retinal imaging plays an important role in the diagnosis of abnormalities and diseases of the retina. Although many kinds of detection and treatment are available, research in this area is still not complete. In this work, a novel algorithm to effectively detect blood vessels has been proposed. For the segmentation of the fundus retina image, the region of interest (ROI) method and extraction of the vein using Kirsch's templates technique are resorted to. For the classification of disease, an artificial neural networks-based firefly clustering algorithm is used. Parameters like cottonwool spots area and the diameter of the vein are used for grouping the affected area. The system has achieved adequate results to support four stages of diabetic retinopathy diagnosis. Accurate detection is successfully determined, notwithstanding the normal or abnormal condition of the retina. MATLAB, a high-performance language for technical computing, is used to implement the concept

Keywords: diabetic retinopathy, firefly, fundus retina image, region of interest.

1. INTRODUCTION

Diabetic retinopathy is a kind of eye condition that arises after several years of sustained high blood sugar (diabetes mellitus). It damages the tiny blood vessels inside the retina, resulting in abnormal leakage of fluid and blood in the eye. If not identified or taken care of, diabetic retinopathy can lead to bleeding, formation of scar tissue, retinal detachment, and blindness.

The retina is a thin layer of delicate nerve tissue. The brain receives images from the retina when light is focused on it. It has two important parts: the Centre, called the macula that provides sharpness, color vision and central vision. The retina, which is at the periphery, is the component that gives us peripheral and night vision.

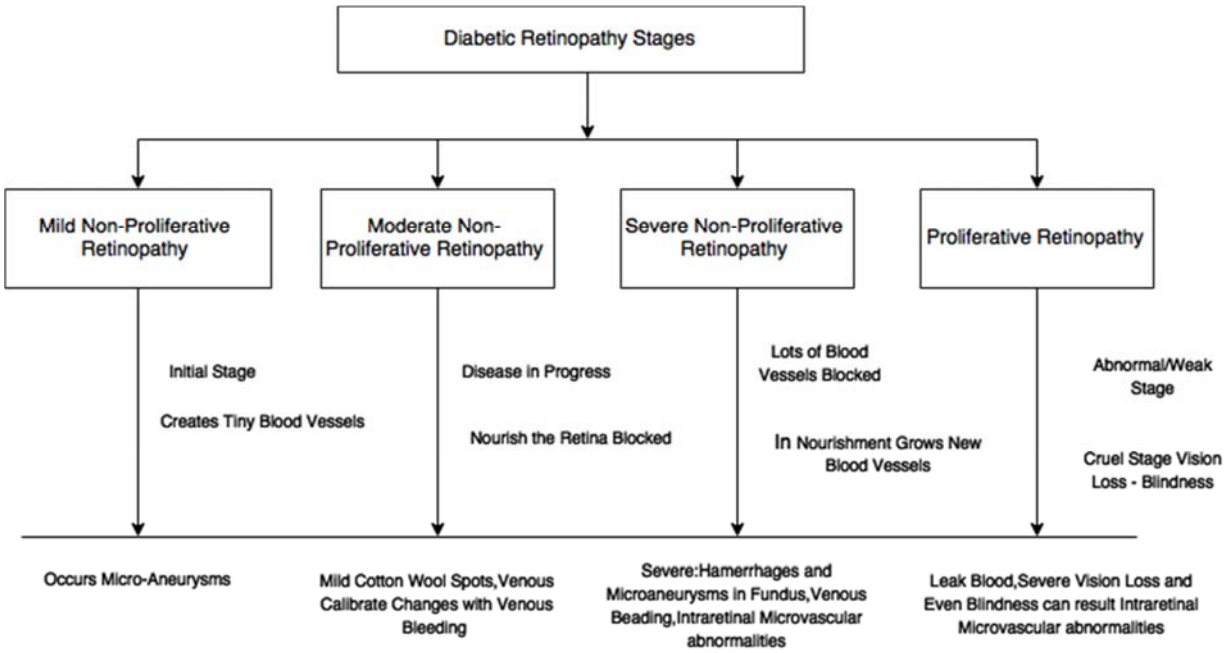
Diabetes mellitus is a collection of conditions described by unusually high blood sugar levels. Thirst, frequent urination and changes in weight are its most common short-term effects. Long-term problems include vision loss, kidney failure, strokes, a loss of feeling in the hands and feet, heart attacks and untimely death. Diabetes mellitus is a major cause of blindness, with numerous studies confirming that careful control of blood sugar levels leads to a decreased risk of blindness and assorted complications. If eye damage caused by diabetes is detected fairly early, laser treatment can save vision, a fact confirmed by the National Eye Institute. The American Diabetes Association recommends annual eye examinations, for all adults with diabetes, to prevent blindness.

Stages of diabetic retinopathy:

a) **Mild non-proliferative retinopathy:** This is characterized by micro-aneurysms, tiny areas of swelling which may look like balloons in the retina's tiny blood vessels.
b) **Moderate non-proliferative retinopathy:** A progression of the disease, wherein a few blood vessels that nurture the retina get blocked if the disease grows.
c) **Severe non-proliferative retinopathy:** This is when several areas of the retina get deprived of blood supply if blood vessels are blocked. These parts of the retina alert the body to produce fresh blood vessels for sustenance.
d) **Proliferative retinopathy:** This is a condition which propels the growth of new and extraordinarily delicate blood vessels at an advanced stage of the disease. The new blood vessels are ranged alongside the retina and on the exterior of the clear found inside the eye. The condition does not lead to vision loss in itself, but since the new blood vessels possess slim and delicate walls, leakage of blood may lead to severe loss of vision and blindness too.

The number of patients with diabetes is dramatically increasing, and worldwide blindness caused by diabetic retinopathy will become more common unless improvements occur in the care process. Two landmark clinical trials, the Diabetic Retinopathy and the Early Treatment Diabetic Retinopathy Study (ETDRS), have

demonstrated that effective treatment for diabetic retinopathy could reduce severe vision loss by 90%. These studies have highlighted that all patients with diabetes should be examined periodically.



Carefully following it up with the timely intervention with laser photocoagulation and vitrectomy is the most efficient method to decrease possible visual disabilities. However, despite the availability of successful treatments, a number of barriers to optimal care remain. These comprise of a variety of financial, sociological, educational and psychological obstructions to normal ophthalmic examinations. In an effort to reduce the visual disability in patients with diabetes, early detection and prompt treatment plays an important role.

The section 1 focuses introduction of the fundus images and diabetic retinopathy in image processing. The section 2 shows related works and section 3 shows proposed works and section 4 gives implantation of the proposed work and final section provides conclusion of the paper.

RELATED WORK

A method to integrate steganography and cryptography for transmitting data securely is discussed. For better safety measures, the image is encrypted using an AES and the encrypted image is hidden using a DWT. Through this, a low MSE and PSNR are attained. A smaller MSE represents improved image quality. For producing enhanced results, diamond encoding seems a good option. Without altering the original cover image, secretly-embedded data can be extracted. The results show that the suggested method not only hides more secret data but also decreases degradation in terms of the quality of the stego-image [1].

Certain ideal methods to hide data in halftone images are studied, and a DHSPT is proposed to hide large data when the original multi-tone image is unavailable. The chance of visually undesirable clusters being formed is minimized by choosing complementary pixels, and experimental results show that high image quality can be maintained. When the original image is available, and if errors are diffused in the halftoning method, an MDHED is proposed which integrates the data-hiding operation with the process of error diffusion. Computationally, both the DHSPT and MDHED are economical [2].

An ideal method for hiding data in palette images is presented. Only image pixels that are classified as data-embeddable are used for embedding secret data. This is based on the use of a new type of color-ordering relationship and, with binary values as output, a color-mapping function is defined A data-embeddable pixel is chosen if a secret bit is embedded, and the color is adjusted to make the color mapping function output equal to the secret bit value. The results show that secret data can be embedded and extracted successfully without producing visual artifacts in the cover image [3].

A novel lossless data-hiding technique that does not generate salt and pepper noise is suggested. A statistical quantity, robust in nature, is recognized and utilized to embed data. By utilizing error rectification codes and permutation schemes, this method accomplishes both losslessness and robustness. It is successfully applied to different images to exhibit its common applications. The results of the suggested technique show that it is reliable and suitable for many applications. This method

can therefore be readily applied to fields where original image recovery is preferred [4].

A new technique for 3-D terrain visualization through a reversible JPEG2000-based blind data hiding is suggested, with a clear spotlight on data synchronization and scalability. For scalability, this study relies on the multi-resolution character of the DWT-based JPEG2000 standard. The coordinated union of the DEM with texture is achieved by applying the perceptual visible data-hiding technique in the domain of the DWT. Only the actual DEM size and the secret key from the image texture are required for data mining in this method. The proposed method is economical in terms of both memory and bandwidth [5].

Even after the extraction of hidden messages without distortion, actual media can be recovered by embedding data into digital media. A data lossless technique is considered by means of which it implants and obtains data in the space domain. A single statistic parameter controlling the mining and embedding of data is used in this technique. In comparison, this novel method significantly increases average embedding, and the PSNR is also simultaneously maintained at a comparable level [6].

Based on logistics and Henon, an encryption algorithm is considered. The idea of the algorithm is to ensure the safekeeping of industrial design images. To produce encryption keys, it utilizes chaotic iteration, and thereafter executes the XOR and cyclic shift procedures on simple text to change the values of the image pixel. Not only does it enhance the safety of the secret keys, but also that of the intermediary cipher text. Hence this scheme is considered to be successful as far as security of industrial design images is concerned [7].

A suggestion to compare the actual text, which exists in bitmap image form, and the image retrieved is tabled by utilizing various fonts of text as a bitmap image. From the stego-image, the actual hot image and description in the text can be retrieved and reconstructed. The reconstructed hot image is roughly distorted by utilizing the usual data-hiding methods. The benefits of applying LSB data-hiding are reliability and unfussiness in implementation, which, however, is not appropriate for binary images. A program in Matlab is devised for encoding text images in a solitary colour image which can be retrieved without difficulty [8].

An algorithm which can enhance the image automatically, by improving the contrast of an input image, is suggested. The algorithm utilizes the Gaussian mixture model to replicate the image's gray-level distribution. An image with equalized contrast is produced by changing the pixel gray intensity in every input period of the appropriate output grey level period. This algorithm proves that it can attain high-quality image equalization even in varied illumination conditions, when compared with the latest methods. It is applicable not only to gray images but also to color images, in spite of parameters not being tuned [9].

A few techniques are considered for various information-hiding applications, as well as to combine the generation of the art image and the hiding of data to improve the mask effect. A novel piece of computer art - known as line-based, Cubism-like imaging - is suggested, which contains the features of typically Cubist art. Whilst creating an image of the input source, key line segments in the image are identified and reorganized to create abstract art. At certain stages in re-coloring, data hiding is executed capably with fewer distortions. Theories have shown that the suggested technique can be reverted to and is helpful in lossless retrieval of art images from stego-images [10].

On the basis of the application of Rubik's cubic algorithm, a novel data-hiding method is pondered over. The idea behind the implementation is that Rubik's cube has 6 faces and in the process of scrambling, it can be divided into 54 (6 faces*3*3) elements. Therefore, an image can form different Rubik's cubic elements, which can be divided into various blocks, based on the 54 units. Data safety can be increased considerably by a combination of Rubik's cubic algorithm and the encryption system [11].

An algorithm with reversible data-hiding mechanism is presented in images of a digital nature. Instead of being sustained with high PSNR values, the algorithm enhances the contrast of the host image to enhance visual quality. Equalization of the histogram can be simultaneously performed by going over the process for embedding data. In addition, actual data can be recovered without adding any more data [12].

Chaos generation in Josephson junctions by numerical simulations is studied so that it can be applied to physical random number generators, Lyapunov exponents, calculated by the Shimada-Nagashima algorithm, were used to review whether or not chaos signals were generated .The possibility of the realization of a random number generator is shown by taking into account real YBCO Josephson junctions. By utilizing the Josephson junction, the product of the random number can be achieved in excess of 50-Gbits/s speed [13].

A new image steganography system in which a secret image is embedded within a cover image, chosen by an improved resilient back-propagation neural network, is presented. This scheme includes embedding and extraction phases. There are 3 main stages in the embedding phase. Using the SOM and ERBP algorithms, the best cover image is set. By separating an image into color layers (red, green, and blue) and then applying the DWT, the secret image is processed, and the ERBP utilized for selecting the best threshold values that are embedded. Through experiments, it was found that the PSNR is well improved [14].

A proper approach that can enable image encryption and decryption efficiently is devised. The special approach to image encryption is in encrypting images without the use of secret keys. This study describes image encryption by utilizing the idea of separation,

division and shuffle. A secret image is split into multiple random images. With this new approach, the actual secret image can be retrieved from random images without loss of image quality and pixel expansion [15].

A selective block encryption technique to protect confidential image data from unauthorized access is discussed and successfully implemented on image data. This algorithm uses selective encryption, which is one of the best ways to decrease the costs and overheads of data protection. Selective block encryption is compared with known symmetric key algorithms in terms of performance. It is found to be faster, and with stronger security features than the others. Hence, in moving data (with privacy and message validation) that is confidential, selective encryption is the most capable and confirmed to be more successful than the others [16].

3. NOVEL ALGORITHM TO DETECT BLOOD VESSELS

3.1 Modified Region of Interest (ROI) method – segmentation for fundus images

There are various reasons, involving a specific set of theories, to execute ROI analyses. In intricate designs - such as factorial designs with many levels - it can be hard, on the whole, to distinguish the prototype of activity across situations. It is helpful to spot the signal in areas of interest plotted for each situation. Functional ROIs are on the basis of data analysis from the same entity. The general approach is to utilize a different 'localizer' scan to detect voxels in a specific anatomical region which shows a specific response.

The following is the procedure for the region of interest (ROI) method for segmentation of fundus images:

Step 1. Based upon the RGB, initial segmentation will be performed.
Step 2. The image is first converted into binary form.
Step 3. The filtering technique is then applied to the binary image.
Step 4. The region of interest technique.is then applied to the image.
Step 5. The centroid of the given image is found.
Step 6. From the centroid, the Euclidean distance for the image is found.
Step 7. Using the centroid, the bifurcation of the image is found.

3.2 Kirsch's templates technique for extraction of veins

The extraction of blood vessels from the enhanced image, based on Kirsch templates, is done. The method involves spatial filtering using templates of different orientations, followed by thresholding. By modifying the threshold value, deviations in the output image can be attained. Utilizing the boundary method, any accomplished results that are unnecessary can be camouflaged.

Retinal blood vessel extraction is a vital step in diagnosing diseases of the eye. As far as oculists are concerned, images of the human retina play a critical part in the detection and diagnosis of various eye diseases. Color retinal images are used to screen general diseases like diabetic retinopathy (DR). The risk of diabetic retinopathy increases with age, and small eye blood vessels are damaged as a result. Information about blood vessels can be helpful in diagnosing symptoms of the disease.

Oculists may inspect retinal images and provide diagnostic results by investigating likely anomalies like diabetic retinopathy, retinal artery occlusion and glaucoma. With the help of computer-aided diagnosis (CAD), the success rate in terms of treatment may increase significantly.

In the past, various techniques were used to extract blood vessels from retinal images. One method was to find blood vessels that began in a group at a major point of origin. The other method utilized a matched filter (MF) for extracting blood vessels and could respond to both vessel and non-vessel edges. The third method was the novel hybrid automatic approach for extraction of retinal image vessels which decreased feeble edges and noise, and finally resulted in blood vessel extraction. This paper proposes a method that utilizes Kirsch's templates for extraction of blood vessels from retinal images.

3.3 Artificial neural networks-based firefly clustering algorithm for disease classification

A meta-heuristic algorithm known as the firefly algorithm (FA) draws inspiration from fireflies because of the way they flash fire. The main reason for flashing fire is to attract other fireflies. Xin-She Yang devised this algorithm, propelled by the belief that fireflies are unisex in nature, so any can be attracted to any other. The attraction is proportional to their intensity: one with lesser brightness will be fascinated bya brighter one. They reciprocate, based on brightness, and move at random if they all are of the same brightness.

3.4 Procedure for the firefly algorithm

Step 1. RETINA vessel size detection in binary pics
Step 2. Read the gray pic and convert it into a binary pic
Step 3. Read the scale of the binary pic
Step 4. Create a color pic as a result for a colored vessel and exactly equal to the binary pic
Step 5. Temporary variables for calculating percentage of each vessel (thickness from 1 to 20 pixels)
Step 6. Vessels are shown by color according to thickness
Step 7. Create a mask according to the thickness of the vessel
Step 8. Compare the mask with vessels and, for detection, vessels are matched with the mask
Step 9. Each thickness is shown by a specific color

Step 10. Colors used for calculating percentage of each thickness
Step 11. Original gray pics are shown
Step 12. Guide map pics, including color guidance and percentage of thickness, are shown.

During the testing time, we used this algorithm to find the level of the disease in the tested image.
Do forever
If status (D(i)) fails, then
Execute the failerHandler procedure for D(i)
Get the next best super peer from the underloaded list based on their rank
Else
Calculate the distance of the disease using firefly algorithm
End if
Calculate_distance_with_classifiedmodel(){
Calculate the fitness values of each image based on its feature values;
While N < # of images_in_model do
If(f(D(j) > (f(D(i)) then
Move D(j) towards D(i)
End if
Update the distance of the image
End while

4. RESULT AND IMPLEMENTATION

The proposed work can be divided into the following four parts: the first part is initial segmentation, with the region of interest (ROI) method used to segment fundus images. The second part focuses on vein classification, based on an implementation of Kirsch's templates technique. Veins are classified along the following lines: moderate non-proliferative retinopathy, non-proliferative retinopathy, proliferative retinopathy and severe non-proliferative retinopathy.

The third part is classified based on the firefly clustering algorithm. The final part focuses on training and testing.

Fundus camera images with dimensions of 545 x 564 (i.e. a width of 545 pixels and a height of 564 pixels) have been used for simulation, with bit depth at 24 pixels and image type a PNG file. MATLAB is used to simulate these fundus images, with the program extracting blood vessels from a retinal image using Kirsch's templates. Spatial filtering of the input retinal image is done with Kirsch's templates in different orientations. The threshold can be varied to fine-tune the output.

For achieving the output, we carried out the 5 consecutive tasks below:

1) Load the image:
   It simply loads the image.
2) Initial segmentation:
   From the extracted pixel of the given image, certain arithmetic calculations are used as the ratio of the pixel that we split into images.
3) Extraction of veins:
   From the segmented image, we simply extract veins.
4) Extracted veins are classified in terms of size.
5) Depending on the size of the vein, we simply classify the stage at which diabetes is.

After detection, we classify those images using a neural network algorithm, which offers easy detection and classification of retinal images.

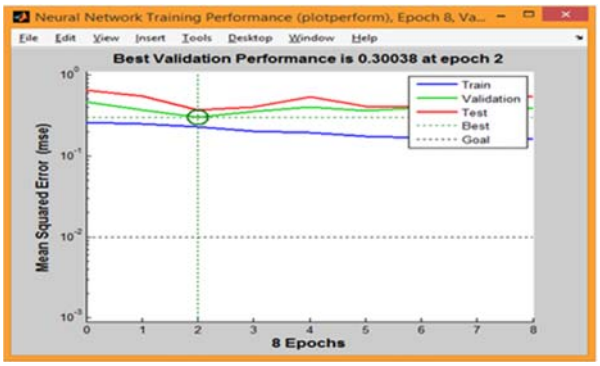


Figure-2. Mean square errors.

Figure-2 explains the epochs on the x-axis and the MSE on the y-axis. The black line indicates a maximum of 100 images with no mean square error. The blue line represents a training state, while the green line indicates validation on training. The red dotted line specifies testing. As per the goal, there is no error. The mu (mean) will increase as per the training. According to the testing, mu value will be high since, in the testing time, the mean square error will also be high.

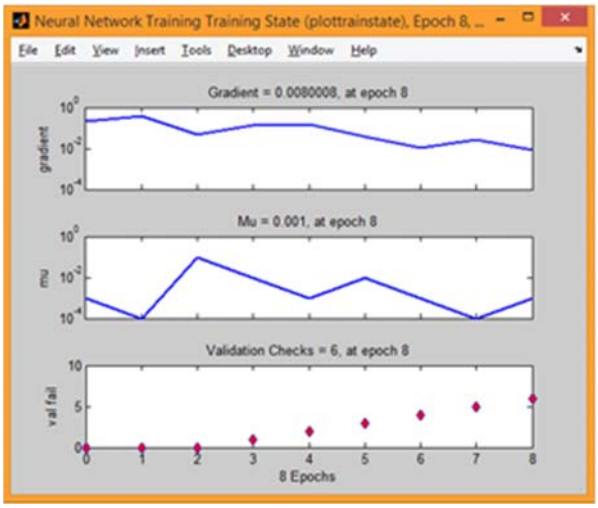


Figure-3. Gradient, Mu (mean) and validation check.

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Figure-3 depicts the training given to the images under the 3 conditions

a) Gradient

b) Mu (mean)

c) Validation checks

If the gradient is 0.008, then the 8 epochs of that image are completed as per the first graph. The gradient will fall if the number of epochs increases. If the mean is 0.001, then the 8 epochs of that image are completed, like in the second graph. The odd number of epochs gives the minimum mean. If the validation check is 6, then the 8 epochs of that image are completed, like in the third graph. If the number of epochs increases, then the validated fail rate will also increase.

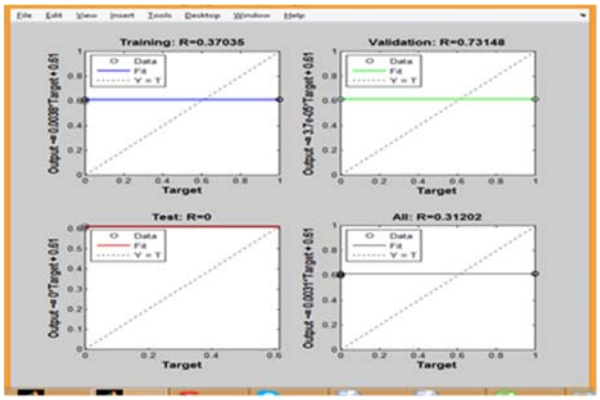

Figure-4. Trained images: Details of disease.

We apply four kinds of regression values for all graphs (Figure-4).

The training regression value = 0.37035 and the constant value is = 0.61, with the maximum target value set at 1. If the target value is 1, then all the training completed is considered successful. Output= (Regression/100) *target + 0.61. The plot target is on the x-axis and output on the y-axis.

Validation

The validation regression value = 0.37148, the constant value is = 0.61 and the maximum target value =1. If the target value is 1, then all validation is successfully completed. Output= (Regression/100) *target + 0.61. The plot target is on the x-axis and output on the y-axis.

Testing

The testing regression value =0 and the constant value is = 0.61. The maximum target value is set as 1. If the target value is 1, then all testing is successfully completed.

Output= (Regression/100) *target + 0.61. The plot target is on the x-axis and output on the y-axis.

All processes

All process regression values =0.31202 and the constant value is = 0.61. The maximum target value is set at 1.If the target value is 1, then all processes are successfully completed.

Output= (Regression/100) *target + 0.61. The plot target is on the x-axis and output on the y-axis.

From the graph above, we have established that the output constant does not vary depending on the number of images and epochs.

Figure-5 represents selected images in Matlab. Veins in these selected images are classified in Figure-6 and Figure-7, helping to arrive at a better understanding of the classification of the disease.

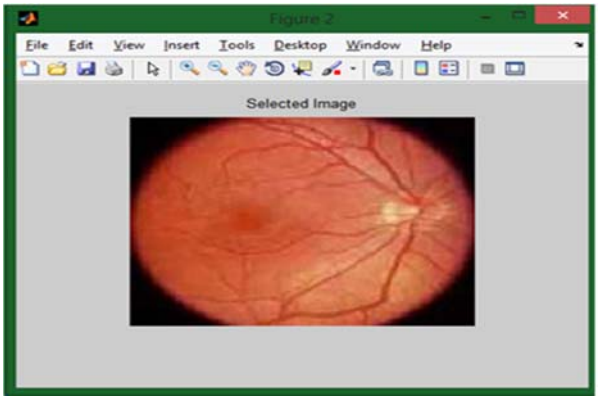

Figure-5. Selected sample fundus image.

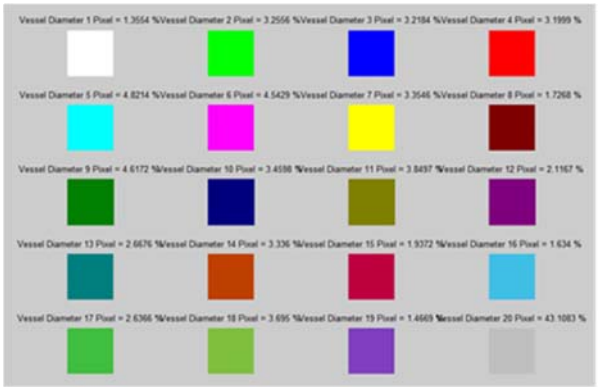

Figure-6. Classifying the vein in fundus image.

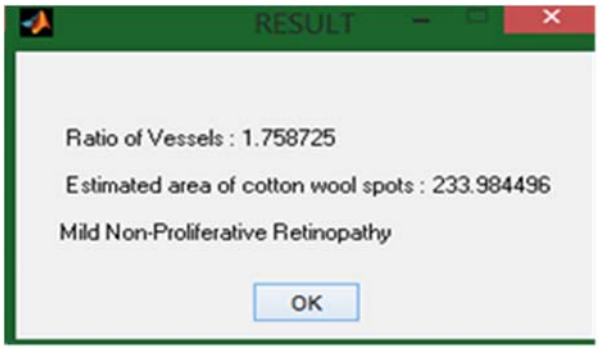

Figure-7. Final results for the classification of the disease.

5. CONCLUSIONS

Thanks largely to the development of novel learning mechanisms competent enough to deal with large-scale learning hurdles; artificial neural networks drew much attention in the past decade. It is easy to extract efficient retinal blood vessels from retinal images using the method above. More than 500 images have been tested, and the method has extracted vessel images successfully. This work proposes a novel algorithm to effectively detect blood vessels. The region of interest (ROI) method is used for retinal images and Kirsch's templates technique is used for the extraction of veins. An artificial neural networks-based firefly clustering algorithm is used to classify the disease. For grouping the affected area, factors like cotton wool spot area and diameter of the vein are considered. The method has achieved sufficient results to support a diagnosis of the four stages of diabetic retinopathy with accurate detection, irrespective of the condition of the retina.

Future studies, focusing on larger samples and prospective clinical trials, are needed for further validation. The present method, tested on artificially and naturally-degraded retinal images, obtained an important enhancement in all cases and it can effectively leverage the significance of these images in clinical practice. Additional tests have to be carried out on the proposed system with more suitable clinical data. Such tests could contribute to greater improvements, resulting in more robust and accurate detection that could eventually be adapted for clinical purposes.

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