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RETINA DISEASE IDENTIFICATION USING IMAGE PROCESSING

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Abstract - *The use of imaging and computer vision systems allows for a quantitative study of human physiology. A recent study has developed an algorithm that combines image processing and machine learning techniques to analyze retinal images and aid in the early detection and diagnosis of retinal diseases. The main aim is to apply these techniques to digital fundus images of the eye to accurately separate diseased eyes from normal ones and improve the speed and accessibility of retinal disease diagnosis and treatment. Automated analysis of retinal images is crucial in diagnostic procedures, and the approach presented in this study utilizes datasets of retinal images to classify over 180 fundus images with lesions and non-lesions, achieving an accuracy of 94.4%, a precision of 94%, a recall and f1-score of 94%, and an AUC of 95%. The proposed approach employs image processing and the Support Vector Machine (SVM) classification method to distinguish diseased eyes from normal eyes using fundus images, thus paving the way for precise and automated classification and diagnosis of retinal diseases.*

Key Words: Retinal image processing, arteries, veins, segmentation, classification, identification.

1. INTRODUCTION

Medical imaging refers to the techniques and processes of visually representing the internal structures of the body for the purpose of analyzing and intervening in health conditions. We aim to clarify hidden internal structures covered by skin and bones, and to diagnose and treat diseases. By creating a database of normal anatomy and physiology, medical imaging can identify abnormalities in various organs of the body. Imaging of excised organs and tissues can be done for medical reasons, but is generally considered part of pathology rather than medical imaging.

In a clinical context, medical imaging using "invisible light" is usually associated with radiology or medical imaging, and radiologists are responsible for understanding and sometimes capturing these images. "Visible light" medical imaging, on the other hand, includes digital video that can be viewed without special equipment. Diagnostic radiography specifically refers to the technical aspects of medical imaging and the acquisition of medical images. Radiologists are usually responsible for obtaining high-quality medical images for diagnosis, but some radiation treatments can be performed by radiologists.

Retinal image processing plays a crucial role in the diagnosis and treatment of various diseases that affect the retina and the choroid. One such disease is diabetic retinopathy, which is a complication of diabetes mellitus that affects the retina and the choroid. The advent of retinal imaging technology has enabled optometrists to capture digital images of the retina, blood vessels, and optic nerve located at the back of the eyes. This has greatly aided in the early detection and management of diseases that can affect both eyes and overall health, such as glaucoma, macular degeneration, diabetes, and hypertension.

With retinal imaging technology, even the slightest changes to the structures at the back of the eyes can be detected. For instance, in choroidal neovascularization (CNV), a network of small blood vessels arises in the choroid and takes away a portion of the blood supplying the retina. As a result, the sight may be degraded and, in severe cases, vision loss may occur. Adaptive Optics (AO) has the potential to facilitate early detection of retinal pathologies. Many researchers have been working on retinal images to perform various image processing tasks for the benefit of the health sector. However, the accuracy of the image analysis depends on the quality of the images, which must have high contrast photoreceptors and vasculature, as well as accurate registration.

Currently, many researchers have developed methods for automatically assessing the quality of retinal images taken by a fundal camera, using a reference image. Recently, AO has been combined with scanning laser ophthalmoscope and optical coherence tomography (OCT) to obtain images of the retinal microvasculature and blood flow, as well as three-dimensional images of living cone photoreceptors respectively.

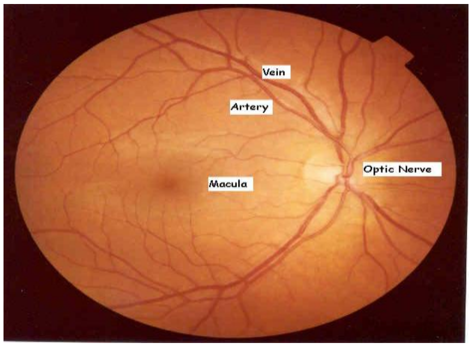

Fig - 1: Blood vessels and optic nerve in a fundus image of retinal image.

Moreover, several studies have shown that incomplete treatment is worse than no treatment, emphasizing the need for an automated laser system to treat the entire retina in a single session. This system is designed to scan and track the retina, applying laser energy to the entire area except for sensitive objects that may be damaged by the energy. The expected functionality of the system is to capture retinal images using a fundus camera and perform accurate segmentation to extract sensitive objects in the retina, such as the blood vessel tree, optic disk, macula, and the region between the optic disk and macula. However, it's important to note that the fundus camera can only provide an image for a portion of the retina and not the entire retina.

2. EXISTING METHODOLOGY

The retinal microvasculature has similar characteristics to vessels in other parts of the body. Imaging techniques can provide non-invasive views of the blood vessels in the retina, making retinal images a useful tool for studying and diagnosing pathologies related to vessel abnormalities, such as hypertension and diabetes. The arterio-venous ratio (AVR) is often used as a marker for diseases, and retinal vessel classification techniques can be categorized as tracking-based or color-based methods. The former requires the labeling of a few vessels by medical experts and requires a vessel tracking algorithm and precise characterization of bifurcation and crossovers.

An unsupervised fuzzy algorithm for vessel tracking has been developed to detect ocular fundus vessels. The algorithm uses linguistic descriptions like "vessel" and "non-vessel" to automatically track the vessels, overcoming problems encountered in previous studies such as initialization and vessel profile modeling.

Fuzzy c-means (FCM) is a soft segmentation technique applicable for medical images. Its performance depends on the initial positions of the cluster centers, the measure of membership degree for each data point, and other factors. The center of the cluster is modified until the discrepancy between successive objective functions becomes significantly smaller than a predetermined small value.

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} U_{ij}^2 \left\| X_i - C_j \right\|^2, U_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_j - c_k \right\|} \right)^2} \quad (1)$$

Where N is the number of features, C is the number of clusters which take as in search. U_{ij} is the degree of the membership of x_i in the cluster j, x_i is the i^{th} of the d-dimensional measured data.

3. PROBLEM ANALYSIS

There are several algorithms proposed for identifying non-vascular lesions and extracting vascular structure in retinal fundus automatic analysis. Changes in the blood vessel structure of the retina can indicate retinopathy, but this can impact arteries and veins differently. To create an automated tool for retinopathy diagnosis and grading, it is essential to distinguish arterial and venous vessels using A/V classification. However, recognizing A/V presents challenges due to variations in inter- and intra-image contrast, luminosity, and color, as well as the fading differences between vessel types in the periphery of the retina. Even after contrast and luminosity normalization, A/V can only be accurately recognized in a region around the optic disc. Vessels inside the optic disc become intertwined, making it difficult for even experts to track, while those in the periphery become thinner and almost indistinguishable.

Furthermore, the reliable recognition of arteries and veins is limited to vessels located close to each other around the optic disc. Vessels far apart from each other may be misclassified based solely on their image features. This applies to both types of vessels, and it is assumed that they are evenly distributed around the optic disc at a short distance from its border. Based on these observations, a strategy was developed to create a dependable A/V classification technique. The first step was to classify vessels within a well-defined concentric zone around the optic disc. The next step was to propagate this classification outside of this area using vessel structure obtained from tracking techniques, where there is little or no information available to differentiate between arteries and veins.

4. PROPOSED METHODOLOGY

The proposed technique employs active contours to eliminate noise, enhance images, track vessel edges, compute vessel perimeters, and detect cardiomyopathies. A graph theory model is used to segment blood vessels and calculate their perimeters. Finally, an effective infinite perimeter active contour model with hybrid region terms is proposed for vessel segmentation, which can be a powerful tool for analyzing the vasculature and managing a range of vascular-related diseases.

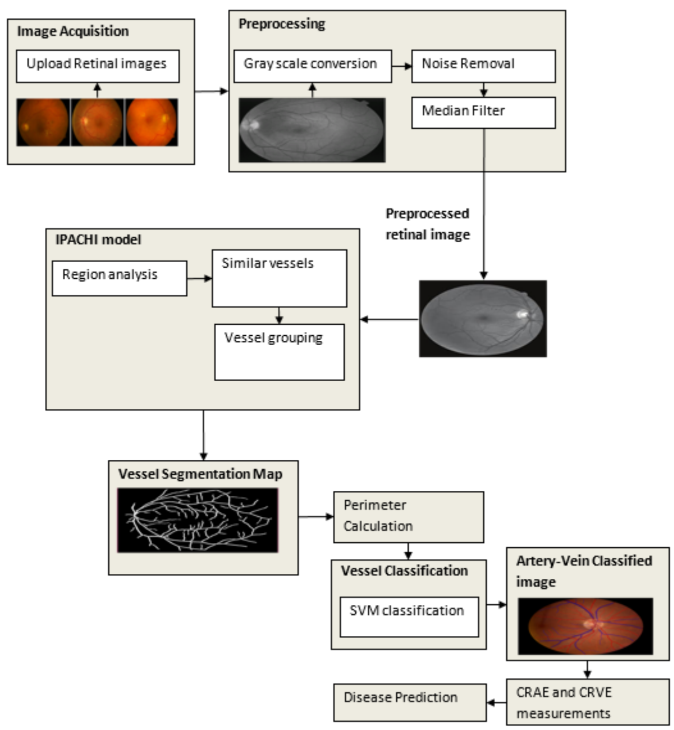

Fig - 2: System Architecture

Examining blood vessels in the eye is a way to detect eye diseases like glaucoma and diabetic retinopathy. In the past, mapping the vascular network required a time-consuming, manual process that demanded training and expertise. Automating this process enables consistency and frees up the time of skilled technicians or doctors who previously performed manual screening. Hence, an automatic process can be implemented to examine blood vessels in retinal images and detect cardio-vascular diseases.

4.1 RETINAL IMAGE ACQUISITION

Detecting and diagnosing cardiovascular diseases is crucial, and the retinal images of humans play a significant role in this process. Common conditions that can be identified through retinal images include stroke, diabetes, arteriosclerosis, cardiovascular diseases, and hypertension. Vascular diseases can be life-threatening for individuals who does not take much care about health and pose a challenging health issues for themselves.

Detecting retinal images is essential, particularly the detection of blood vessels, which is the most important aspect. Changes in blood vessels, such as length, width, and branching pattern, can provide information about pathological changes and help to assess the severity of diseases or automatically diagnose them. In this module, we upload retinal images, which show the interior surface of the eye, including the retina, optic disc, macula, fovea, and posterior pole.

The retina is composed of layers of interconnected neurons with synapses and contains blood vessels that may exhibit abnormalities and alterations at an early stage. These abnormalities are often expressed through the arteriolar-to-venular diameter ratio, which is associated with higher blood pressure levels. To develop and test our proposed method, we constructed an image dataset using publicly available datasets like DRIVE and STAR. Each image in the dataset was captured at a resolution of 760 x 570 pixels with 24 bits per pixel. Initially, the proposed method was tested on normal images, which are easier to differentiate, and further testing is needed to establish its effectiveness in identifying abnormal vessel appearances. Abnormal images typically contain multiple artifacts of varying shapes and colors caused by different diseases, in addition to the blood vessels, optic disc, fovea, and background.

4.2 PREPROCESSING

This module involves converting colored retinal images to grayscale to detect black-and-white illumination. Noise in colored retinal images is usually caused by noisy or distorted pixels. To preprocess and segment retinal images, a sharpening filter can be implemented to enhance and sharpen the vascular pattern, resulting in effective preprocessing, enhancement, and segmentation.

Human perception is highly sensitive to the edges and fine details of an image, which are mainly composed of high-frequency components. If the high frequencies are attenuated or removed, the visual quality of an image can be severely degraded. On the other hand, enhancing the high-frequency components of an image can improve its visual quality.

Enhancing the edges and the fine details of an image can be done using the Image sharpening techniques. This will interferes in adding a signal to the original image that is proportional to a high-pass filtered image of the original image. The high-pass filter extracts the high-frequency components of the original image, and a scaled version of the high-pass filter output is added to the original image to produce a sharpened version. The homogeneous regions of the image, where the signal is constant, remain unchanged.

4.3 VESSEL SEGMENTATION

In this section, a graph theoretical model is employed to perform feature extraction and vessel segmentation. The model utilizes an active contour, nearest neighbor measure, and neighborhood function to create a vascular network. A map is used to depict the network, where every intersection point in the vascular tree is denoted by a node, and each vessel segment connecting two intersection points is indicated by a link. To generate the graph, an active contour method is used to extract nodes from the centerline image. Bifurcation points are identified by considering pixels with more than two neighbors, while endpoints or terminal points are identified by pixels having just one neighbor. The links between nodes are found by removing all bifurcation points and their neighbors from the centerline image, resulting in an image with separate components that represent vessel segments.

The binary mask for vessel segmentation is generated by identifying the edges of the vessels from the sharpened image. The blood vessels are marked by assigning the value of one to the pixels that belong to the vessels and zero to those that do not. A final refined vessel segmentation mask is produced using an active contour model, which is also known as snakes. Snakes are deformable splines that minimize energy and are influenced by constraints and image forces that guide them towards object contours, while also resisting deformation. They are a specific technique within the broader approach of matching deformable models to images through energy minimization. In two dimensions, the active shape model is a discrete version of this approach that leverages the point distribution model to limit the shape range to a specific domain learned from a training set. Ultimately, the segmentation mask is provided for the preprocessed retinal images.

4.4 VESSEL CLASSIFICATION

The blood vessels are divided into arteries and veins for correct analysis of heart diseases, which affect them differently. The extraction of blood vessels leads to the creation of a feature vector based on the properties of arteries and veins. This vector is generated from the centerline extracted image, with each centerline labeled as either an artery or vein pixel. The final goal is to assign the A/V classes to each label using SVM classification, which utilizes both structural and intensity information. To allow the final classification between the arteries and veins along with the vessel intensity information has to be used. The trained classifier is then used to assign A/V classes to each (C_{ij} , j = 1, 2) sub-graph label i, with the probability of a label that can be an artery calculated based on the number of integrated centerline pixels classified by the LDA. The probability for an artery with the label C_{ij} is

$$P_a (C_{ij}) = n_a C_{ij} / (n_a C_{ij} + n_v C_{ij}) \quad - (2)$$

Where $n_a C_{ij}$ is the number of centerline pixels of a label classified as an artery and $n_v C_{ij}$ is the number of centerline pixels classified as a vein. Each subgraph will have labels for pairs of categories, and the label with the greater likelihood of being an artery will be classified as such, while the other label will be classified as a vein. In order to avoid incorrect classifications caused by inaccurate graph analysis, we will calculate the probability of each individual link being an artery or a vein.

4.5 DISEASE DIAGNOSIS

This module uses the AVR ratio, which is based on measurements of CRAE and CRVE, to diagnose diseases. These measurements are real, positive numbers that have been found to be correlated with cardiovascular disease risk factors. Smaller CRAE is primarily determined by higher blood pressure, while wider CRVE is mainly caused by current smoking, higher blood pressure, inflammation, and obesity. Individuals with higher blood pressure have, on average, smaller CRAE and wider CRVE, with an average of 4.8 microns to 2.6 microns, than those with lower blood pressure. A recent study found a strong negative correlation between renal function and retinal parameters (CRAE and CRVE) in healthy individuals, indicating a shared determinant in pre-clinical organ damage. CRAE is useful in predicting hypertension as well as other conditions like stroke and diabetes. Narrowing of arterioles, as indicated by a decrease in CRAE, is associated with an increased risk of stroke, while an increase in CRVE is linked to diabetic retinopathy, its progression, proliferative DR, and macular edema in diabetes patients but has no correlation with CRAE.

5. ALGORITHM

5.1 GRAPH THEORITICAL MODEL

This project introduces a novel approach to segmenting images with uneven object boundaries that have constant color values. The proposed method is a modification of the region information technique. The objective is to preserve the intricate details and irregularities of the object boundaries while also removing any additional Gaussian noise present in the image. The model's energy is given by:

$$F(\tau, r_n) = L^2(\gamma - \tau) + \sum_{n=1}^{N} \lambda_n R_n \qquad - (3)$$

Where L^2 is the 2D Lebesgue measure, R_n is the information of nth region and N is the total number of different region terms. L^2 is the first term that gives the area of γ neighborhood of the edge set τ. Here we consider $L^2(\gamma - \tau) \approx \int_{\Omega}^{\alpha} e^{-(\frac{\phi(X)}{\gamma})^{\alpha}}$ for an even and large number α which is an approximation of the γ neighborhood area of the given image $U_0(X)$.

5.2 SUPPORT VECTOR MACHINE

The SVM classifier is used for classification. Over the years, SVM classifiers have proven to be highly effective in solving a range of pattern recognition problems. The input space is transformed into a feature space with high dimensions. Then, a hyperplane is constructed that maximizes the separation margin between classes. The points that are nearest to the decision surface are identified as support vectors, and their location plays a direct role in classification. When classes cannot be separated, the optimal hyperplane is the one that minimizes the probability of classification error. The initial input image is converted into feature vectors.

Next, the feature vectors are transformed into the feature space using a kernel function, and the classes in the training data are separated by computing a division in the feature space. To prevent overfitting and accurately divide the training examples, an SVM requires a global hyperplane. This SVM phenomenon is superior to other artificial intelligence-based machine learning techniques. In this study, the width of the vessels is an essential feature for classification. By using the SVM classifier, the vessels can be efficiently separated into arteries and veins.

SVMs possess several appealing characteristics, such as superior generalization ability compared to other classifiers. Moreover, they have fewer parameters to adjust, and it is not necessary to determine the architecture experimentally. The SVM algorithm separates input pattern classes using a hyperplane with a maximum margin. The construction of this hyperplane involves:

$$f(x) = \langle w, x \rangle + b \qquad - (4)$$

Where the feature vector is given by x and w is the vector that is perpendicular to the hyper plane. $b\|w\|^{-1}$ Specifies the offset from the beginning of the coordinate system. To leverage the advantages of non-linear decision boundaries, the separation is conducted in a feature space F that is established by a non-linear mapping of the input patterns through φ. The mapping is defined as follows:

$$\langle \varphi(x_1), \varphi(x_2) \rangle = K(x_1, x_2)\ \forall (x_1, x_2) \in X \qquad - (5)$$

The transformation of the original feature space into F is represented by the kernel function. Afterward, we can use the Artery vein ratio as a parameter to examine retinal vascular geometry, which is a high-quality measure. This measure was developed to determine the ratio between the normal diameters of the arterioles and venules and consists of two components: the central retinal artery equivalent (CRAE) and the central retinal vein equivalent (CRVE). These components are expressed as a quotient and are calculated by iteratively combining the mean widths of consecutive pairs of vessels in the arteries and veins, respectively as follows:

$$CRAE = 0.88 * (w_1^2 + w_2^2)^{\frac{1}{2}} \qquad - (6)$$

$$CRVE = 0.95 * (w_1^2 + w_2^2)^{\frac{1}{2}} \qquad - (7)$$

Where $w_{1,}\ w_{2,}$ a pair of width values, then Artery vein ratio can be calculated as,

$$AVR = \frac{CRAE}{CRVE} \qquad - (8)$$

6. RESULTS AND ANALYSIS STUDY

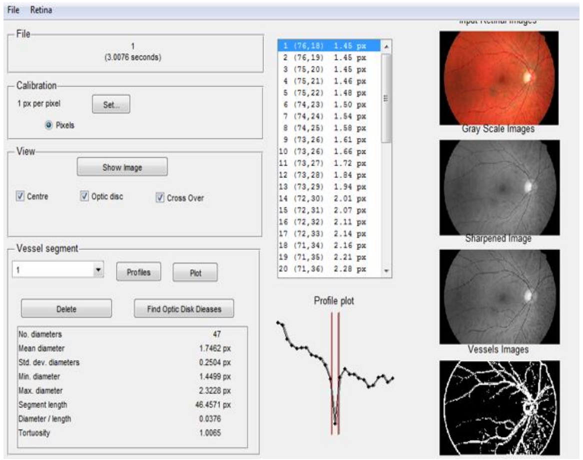

Fig - 3: Graphical user interface for showing results in Matlab.

Fig - 4: Gray scale conversion of input image.

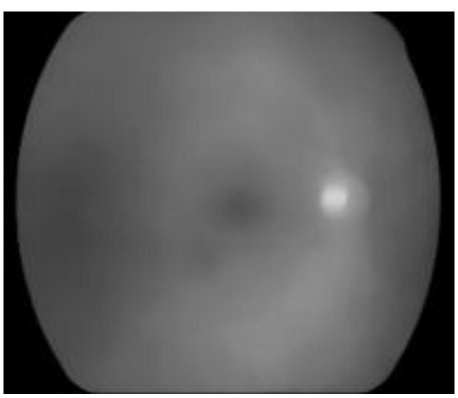

Fig - 5: Median Filtered image.

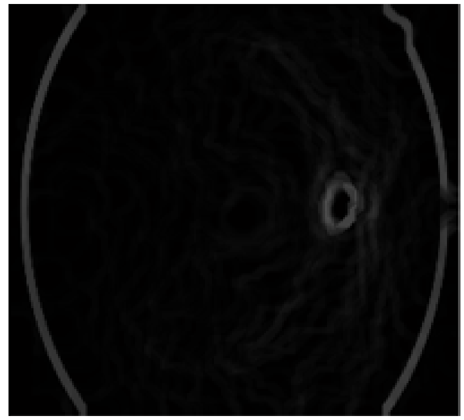

Fig - 6: Morphological Gradient of image.

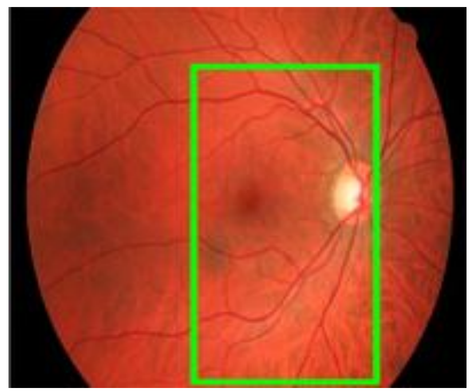

Fig - 7: Bounding box of the disc.

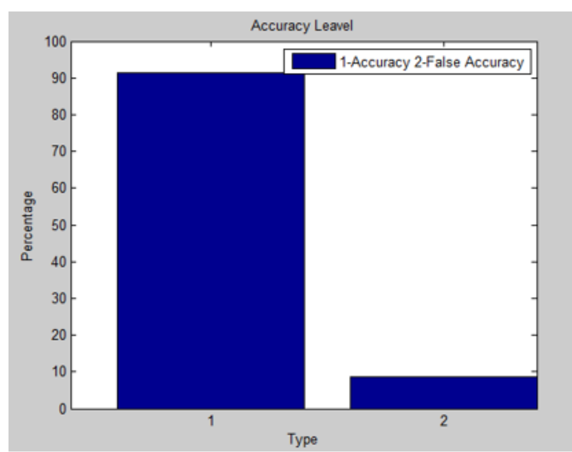

Fig - 8: Accuracy level of the Algorithm

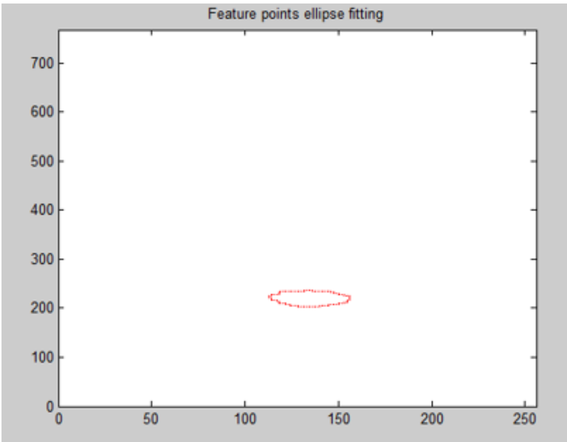

Chart - 1: Feature point's ellipse fitting showing the results of the algorithm after running the trained datasets.

To test the effectiveness of our proposed method, we implemented it using MATLAB 2012b on a system with an i3 processor and 4GB RAM. We used two sets of images for validation purposes. The first set contained six different images with six different diseases selected from planet Earth, while the second set consisted of approximately eight images. The results are divided into two categories: (A) correctly identifying the infected area or disease on the plant leaf, and (B) classifying the type of leaf disease. To evaluate the performance of our proposed method in correctly identifying the affected area or disease on the plant leaf, we used two quantitative evaluation parameters based on the statistical performance of the ground truth image and the segmented image. The most crucial aspect of our work is the classification of diseases. We assessed the performance of our proposed method in correctly classifying diseases by utilizing two entropy functions: the validation evaluation partition coefficient (Vpc) and the validation evaluation partition entropy (Vpe).

$$Specificity=TNTN+FP \qquad - (1)$$

$$Sensitivity=TPTP+FN \qquad - (2)$$

Where, True Positive (TP) refers to the number of pixels that are correctly classified, while False Positive (FP) refers to the number of pixels that are incorrectly classified. True Negative (TN) represents the number of pixels that are correctly misclassified, and False Negative (FN) represents the number of pixels that are incorrectly misclassified. The sensitivity and specificity values range between 0 and 1, with a result of 1 indicating perfect segmentation.

$$Vpc= \Sigma\Sigma uik2NNi =1Kk=1 \qquad - (3)$$

$$Vpe= -\Sigma\Sigma uik\log (uik) = 1Kk=1 \qquad - (4)$$

7. CONCLUSION

In conclusion, our proposed system was successfully implemented and accurately identified true vessels to obtain correct retinal ophthalmology measurements. We implemented a post-processing step to segment vessels, which tracked all true vessels and found the optimal ones, thereby overcoming the issue of wrong diagnosis of crossovers by simultaneously identifying blood vessels from the retina. The ultimate aim of our proposed method is to facilitate the early detection of diseases related to the blood vessels of the retina. Its main advantage is its full automation, which does not require any intervention by clinicians and releases necessary resources (specialists), thereby reducing consultation time and facilitating its use in primary care. We also recognized that the classification of arteries and veins in retinal images is crucial for the automatic assessment of vascular changes. Our graph theoretical method, combined with Support Vector Machines (SVM), outperformed the accuracy of the SVM classifier by incorporating intensity features, demonstrating the significance of using structural information for A/V classification. Furthermore, we compared the performance of our approach with other recently proposed methods and concluded that our method achieved better results.

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