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Extracting Features and Classifying Images of Retinal Blood Vessels using the Firefly Algorithm and Artificial Neural Network

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Abstract— **Various eye diseases as well as cardiovascular and cerebrovascular diseases can affect retinal blood vessels differently, such as shape distortion and bleeding. In recent years, retinal vessel segmentation techniques have been used to diagnose various eye diseases. For retinal vessel segmentation algorithms, there are essentially two categories: supervised and unsupervised methods. Unsupervised methods rely on rule-based segmentation algorithms such as filtering, vessel tracking, and morphological methods. However, they lack generalizability, leading to the formation of false edges in the retina. Among supervised algorithms, image processing and optimization-based methods are used to process retinal images.**

This article proposes a multi-scale network based on the wormhole search algorithm to address problems in current retinal vessel segmentation methods. Specifically, it presents a wormhole-based feature extraction method that prevents scattering and degradation in retina images while effectively extracting image details. At the same time, information from different levels of the network is combined and short-range features are used. This method collects low-level and high-level feature information, effectively improving the segmentation performance. Experimental results show that the proposed method achieves 93% classification accuracy on the DRIVE dataset and outperforms previous methods.

Keywords: ECG; Electrocardiogram; Particle Swarm Optimization, Metaheuristic Algorithms, Predicting Eye Disorders, Deep Learning Techniques, Neural Networks, Firefly Algorithm, Retina.

I. Introduction

Among all the organs in the human body, eyes provide us with the best sense, giving us the opportunity to see beauty and establish visual communication with others. Clear vision plays a vital role in our lives. However, due to different eye diseases, preserving healthy vision is sometimes crucial. Therefore, it is important to regularly examine the different parts of the eye. Among the different components, the retina is the most important element that can show signs of various visual impairments. The various morphological properties of retinal blood vessels, such as branching pattern, length, tortuosity, angular features, and first observed area diameter, are the key factors in identifying any ocular disease. Studies have shown that high blood pressure can be classified by narrow arteries with bright reflexes. Branching, central light reflex, deliberate branching, and contrast changes in blood vessels are usually general causes of incomplete separation of retinal blood vessels from color images. Accurate classification of retinal blood vessels is a challenging task for determining primary visual problems. However, in recent years, computer-aided diagnostic systems have used vision and analysis techniques such as retinal imaging, ultrasonography (USG), and computed tomography (CT). High-resolution images inside the retina can help ophthalmologists automatically detect retinal blood vessels, optic disc, and other disorders. Fundus images provide many features such as retinal vessels, optic discs, and macula. A sample of the retinal fundus image can be seen in figure 1A. Retinal vessels distributed throughout the retina play an important role in diagnosing various diseases such as diabetic retinopathy, glaucoma, arterial sclerosis, and high blood pressure. Moreover, retinal blood vessels are the primary determinant of locating other major structures of retina and provide many measurable features for diagnosing eye diseases. Therefore, extracting retinal vessels is essential for diagnosing and treating retinal diseases. Extracting retinal blood vessels is a binary map process in which retinal blood vessels are labeled as white and the background pixels of the retina are labeled either black or vice versa. A sample two-class map that has been manually labeled by an expert is shown in figure 1B. The ideal goal of many studies in this field is to obtain a binary vessel image by an automatic computer algorithm. Extracting retinal vessels involves challenges such as pathological diseases and noise observed in retinal images. It has also been observed that retinal images have a low contrast between retinal blood vessels and retinal background. Different methods have been proposed to perform these challenges in studies. Feature extraction solutions can be divided into rule-based and machine learning-based methods. In image processing-based methods, a pixel is labeled as a vessel by some predefined criteria. These methods include 2D matched filter response, morphology-based approaches, and tracking-based methods.

Machine learning methods include supervised and unsupervised classifications. By using features that distinguish vessels from retinal background, a pixel is labeled as a vessel or background.

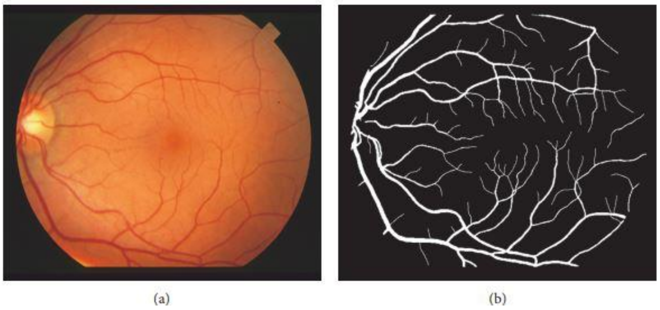

Fig 1 : An example of a color image of the retinal fundus and a map of bilateral vessels divided by hand [1].

II. RESEARCH THEORETICAL FRAMEWORK

In recent years, various methods have been proposed and implemented for extracting retinal vessels from images. One widely used method is the matched filter, which was first proposed by researchers in 1989 and later expanded upon in 2000. Typically, these detection methods use a two-dimensional linear structuring element that is Gaussian. The resulting image is then thresholded to create a binary segmentation of the vessels. However, this method does not always identify junctions in identified vessels, misses small vessels, and does not verify the credibility of identified vessels. Additionally, selecting the threshold is critical to the classification of vital images.

To improve the performance of the conventional matched filter, in 2007, an improved matched filter was proposed using an optimization method to search for the best parameters. Another method for extracting vessels is the vessel tracking method, in which three characteristics (orientation, width, and central distribution of the cross-section of blood vessels estimated using a Gaussian shape) are used to determine each vessel segment. Individual segments are identified using a search method that tracks the center of the retina and makes decisions about the path of detecting retinal disorders based on the extracted features.

Recently, some researchers have used neural networks, as well as K-nearest neighbor classification, to divide vessels by pixel classification of retinal images as blood vessels or non-blood vessels.

In their article, Mr. Rafsanjani and his colleagues presented a comprehensive experiment on two sets of color retinal images using the retinal vessel segmentation approach, in which a four-dimensional feature vector was created using a bundle transform. In this study, retinal blood vessel segmentation was performed with 95% accuracy, which is promising compared to other studies.

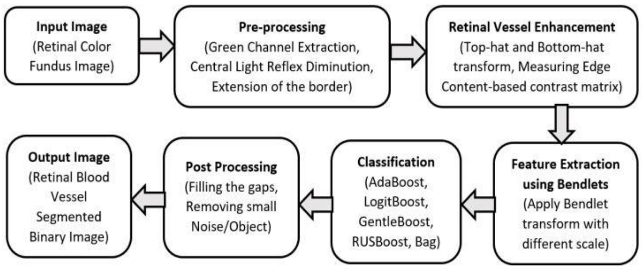

Fig 2: It shows the schematic of image processing in the extraction of blood vessels [1].

Proposed methods for extracting retinal blood vessels consist of three phases of preprocessing, classification, and postprocessing. In order to extract the vessels, the green channel of RGB image goes through various stages. The green channel is selected because the red and blue channels have lower brightness. Figures 2a and 2b show the original RGB image and the green channel, respectively. All three phases responsible for extracting retinal blood vessels are explained below.

In the article, Jiotisparva and his colleagues presented a computer technique for extracting retinal blood vessels from fundus images, which is performed in three phases: (a) preprocessing, in which the image is enhanced using adaptive histogram equalization with limited contrast and median filter, (b) classification, using mean threshold C to extract retinal blood vessels, and (c) postprocessing, in which a separation operation is performed to remove isolated pixels. The performance of the proposed method and experimental results show that the proposed method achieved an accuracy of 95.0% for extracting retinal blood vessels from digital retinal images.

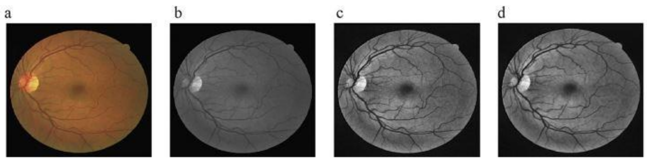

Fig 3: (a) original retinal image, (b) extracted green channel image, (c) equalized image of adaptive histogram with limited contrast and (d) median filtered image [4].

- Division of Retinal Vessels

One of the main tasks of manual classification of retinal blood vessels is performed by qualified ophthalmologists to separate the vessels from their background for further clinical evaluation. However, the manual classification process is time-consuming and also prone to errors. Computerized classification methods have shown good progress in vessel segmentation by using image processing, computer vision, machine learning, and pattern recognition. The main task of image processing for retina is vessel segmentation.

In the study conducted by Munsurit et al, a method for extracting retinal blood vessels using optimized Gabor filter was presented. Gabor filters are a set of orientation and frequency-sensitive bandpass filters that have optimal localization properties in both low and high-frequency patterns. They start with an RGB retina image and extract the green channel, apply an adaptive histogram equalization, and transform it to a grayscale and binary image. They used certain sizes for the median filter to reduce noise, and a length filter to remove disconnected pixels using the concept of connectivity in the binary image. They quantified their results by comparing true positives and false negatives.

- Image processing

In many image segmentation studies, a classification-based approach has been used. Each pixel in the fundus image is classified using a weak supervised learning algorithm as either a vessel or non-vessel. Pixel classification is based on local photometric or geometrical changes in the fundus image. Also, geometric alterations are considered by changes in the vessel pattern. Although many of these features are also used by some existing vessel segmentation algorithms, in this study, the vessels, background, and pathological structures are determined using certain texton distributions. This departs from traditional approaches and demonstrates the high modeling power of textons for object detection.
In the training phase, each patch in the training image is either labeled as a positive sample of vessel or a negative sample of non-vessel, and the textons are extracted from both target and non-target regions in the retina images. Non-target regions' textons are used as negative samples during the learning process. Texture mapping technique is used for vessel segmentation in new fundus images.
For each location in the new image, a bank of filters is applied. By using the filter response vectors, the given location is mapped to the corresponding texton id by finding the cluster center closest to the filter response vector in the feature space. Each pixel location is then classified as either a vessel or non-vessel based on the filter responses and results obtained from the texton library created in the training phase.
Three different sets of filters have been proposed for texton-based analysis of general tissue surfaces. Researchers recommended a set of 48 filters; 36 large filters (3 scales, 6 orientations, and 2 phases), 8 medium Gaussian filters, and 4 lowpass filters. The vectors (formed at each pixel location in the training image) are then clustered to find K centers, such that the sum of distances to the centers and the vectors marked with the centers are minimized.
Note: The translation might not be 100% accurate, since the original text is a technical one and contains some professional terminology.

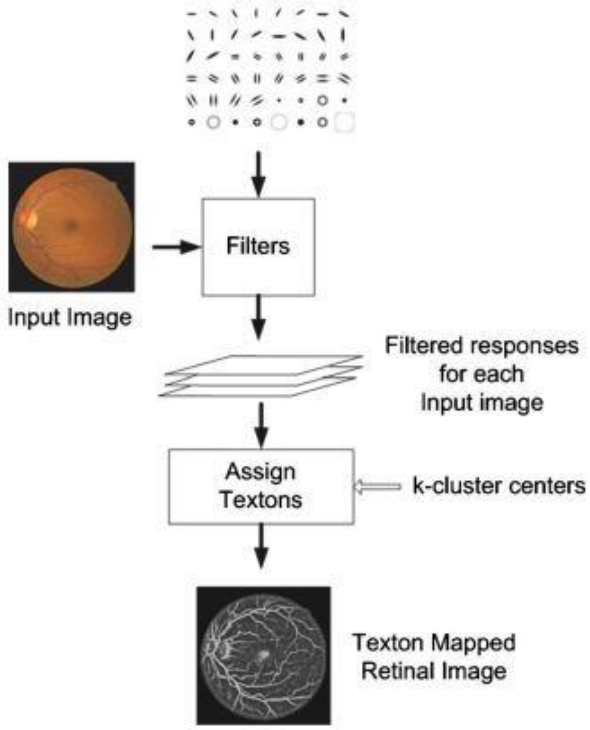

Fig 4: The method presented in texton [7].

Improving the classification of retinal images is always a challenging task and one of the primary responsibilities of image processing. The features of retinal images make their classification more difficult. Therefore, there is a need for an appropriate method to enhance retinal images. Nowadays, various methods for image enhancement exist, classified as shown in Figure 5. Different approaches have been suggested by many researchers to improve the images, but they are not always effective and have only slightly improved in the area of enhancement.

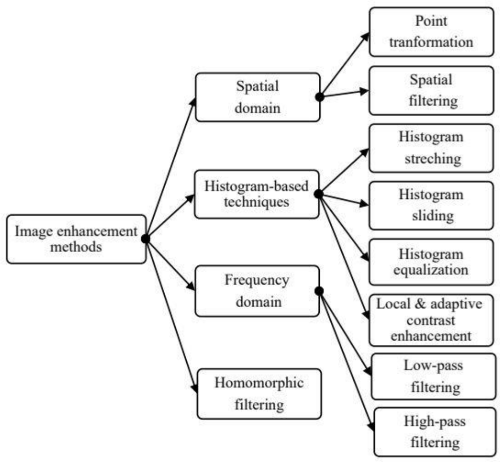

Fig 5: It shows the image improvement techniques in classification [8].

III. Suggested approach

- ***Modeling the image segmentation method***

Optimization results of parameter tuning were used for a set of models, providing the potential to predict the parameters of classification methods for new databases. In the image segmentation modeling approach, first, by optimizing the performance of the classifier algorithms, we compare their performance using the input dataset. The dataset is divided into training and testing data, and the data is applied as an input to the classifier.

The first step in building a machine learning model is to gather training/testing data from the dataset. For supervised classification problems, the data must be labeled. The main issue to evaluate is the training set should be a matrix in which each row represents a modeling error, and the number of columns corresponds to the features that you indicate. These columns are numeric values only. A class label vector should exist which has a width of 1 column and includes the numbers related to each class of data, where 1 represents noisy images and 0 represents non-noisy images.

Usually, during the training of a model, the data is collected in a single set, which is randomly divided into a training set and a validation set. Typically, about 70% of the data is used to train the model, and the remaining 30% is used for testing (model evaluation).

- ***Optimization and performance comparison***

The performance of each algorithm was evaluated using manual segmentation of the first database (in alphabetical order) as a reference and using MCC, Acc, Sn, Sp, and AUC as performance evaluation criteria. For the STARE database, images were preprocessed for edge detection. Here, the criteria are expressed as percentages. If two manual segmentation sets are provided for a database, the performance of the second observer (second manual segmentation) is evaluated and compared with the performance of automated methods. A neural network was employed to find the best segmentation performance in a subspace created by a Cartesian vector on sampled parameter values. Here, we discuss the details of each approach that differs from the standard neural network search method.

The worm-shape approach was used to determine the parameter settings for the classifiers through initial experiments. To search for the best image, an optimization approach was employed to prevent the assessment of poor images. As a result, comprehensive parameter searches require performance evaluations in numerous points. It was thus decided to examine parameter performance separately or at a random select point. The defined ranges were then followed only in the direction of the parameter axes as long as performance improvements were observed, and the entire method was repeated from the best observed point.

- ***Training Data***

Subsets of databases were used as training data to optimize parameters and train the classifier using the worm-shape approach. The number of training images for each database was different: the DRIVE database was used to create a specific training set. With STARE, each database was randomly divided into two subsets of equal lengths, and each subset was used to train a classifier. Next, each of the classifiers was used to classify images from the other training subset.

- ***Image Processing***

Two different approaches to preprocess retinal images at the input were identified among the methods. The first is the "only pad" preprocessing approach, which covers the image edges and is part of the worm-shape method. The second approach is the adaptive histogram contrast preprocessing approach in which the image appears as above. This approach is part of the feature extraction execution. With image preprocessing, before applying the algorithm used to increase resolution and filter retinal images with parts in each image, images are added to the edges [9].

- ***Firefly Algorithm***

The firefly algorithm is an optimization algorithm that mimics the behavior of worm-like creatures. The algorithm includes rules that describe the behavior of firefly creatures, which are listed below [10]:

• Regardless of gender, all worm-shape creatures attract each other.

• Each firefly creature is attracted to others based on its brightness and distance from them. A less bright worm-shape creature moves towards a brighter one. Attractiveness decreases with an increase in distance between firefly creatures. If a firefly creature is luminous, it randomly moves.

• The brightness of firefly creatures is determined by their fitness function.

• The steps of the binary firefly algorithm are shown below, inspired by the study [10]:

A population of 20 worm-shape creatures with 100 values (100 features exist in the dataset) divided into 20 subsets, is created. These 100 values are made up of 0 and 1. 0 represents an unselected feature, and 1 represents a selected feature. Table 1 shows an example of the firefly algorithm proposed by [10]. In this table, f stands for worm-shape creatures (subsets of features), and F stands for dataset features. For example, as indicated in Table 1, F1, F3, and F4 are features for F1 that are not selected. Worm-shape creatures mean that these features are only removed from the dataset when used for training or testing purposes.

Each firefly creature (subsets of features) has a fitness function value, shown in the equation below [10].

$$FitFunc = w * acc(f_i) + (1 - w) * \frac{\sum C_i}{\sum C_i}$$

In the above equation, w is a constant value and is the accuracy value of the firefly with subset features. K-Nearest Neighbor classification is used to obtain accuracy values. A validation set is used for training. Then, with a test set, the accuracy values for all fireflies are obtained. The expression is the total number of selected firefly features and the expression is the total number of firefly features, which is equal to the total number of features in the data set.

Table 1 : Shows the firefly algorithm [10].

```
while iteration < maximum iteration
  for i = 1 to n (n = number of fireflies)
    for j = 1 to n (n = number of fireflies)
      if fitfunc_i < fitfunc_j
        move i^th firefly towards j^th firefly with the Equation (2)
        apply Equation (6)–(7)
      else
        move i^th firefly randomly with the Equation (5)
        apply Equation (6)–(7)
      end if
      calculate new fitness function value of new i^th firefly with the Equation (1)
    end for
  end for
  rank the fireflies (subset features) according to their fitness function values
end while
Obtain the firefly (subset features) which has the maximum fitness function value
```

We combined four extractor features. 100 features are obtained with these four feature extractors. In order to reduce the time in classification training and obtain the best features from each feature extractor, the firefly optimization algorithm has been used in this study. The firefly algorithm was developed for continuous optimization problems [10]. As we need it to select the feature, binary firefly algorithm is used. The goal of this algorithm is to obtain the highest accuracy value with the lowest feature.

IV. Analysis

In this section, an approach for automating the edge measurement of images and its evaluation on a new retinal database is proposed. This approach includes the use of image segmentation methods in the database, separating images individually.

The database used in this work is based on a population-based follow-up cohort study on risk factors for type 2 diabetes and screening for abnormal glucose metabolism in primary health care. This study includes adults born between the ages of 25 and 65. Retinal photographs were recorded and received during the patients' visits. In total, the retinal images of 15 participants in this study were obtained, and the images were processed in MATLAB software.

Included in the database are RGB color photographs stored in JPEG format with a color depth of 8 bits per color channel. Four retinal photographs were recorded and studied for each person.

From the clinical parameters measured in this study, systolic and diastolic blood pressure, age, BMI were made available for use in the presented work.

The scorer was blinded to the characteristics and endpoints when performing the measurements. Preferably, the images of the right eye were measured. When the image was not of sufficient quality, the image of the left eye was used.

- ***method***

In this section, the application of image segmentation prediction is explained. The used method is used to identify the divided edges and measure the width of the images.

Manual segmentation of retinal vessels was not available for the used database, and therefore, methods for vessel segmentation and prediction of their parameters were performed in order to obtain image segmentation. Also, a combination of segmentation methods and prediction models of their parameters were tested. The firefly method for extracting image features was chosen for testing because it provides better performance and does not have any training examples.

Model selection was done to predict the parameters of the method and evaluate it by comparing the quality and segmentation obtained using a subset of the described models. Models based on the following sets of predictors were tested:

It shows the measurement used to optimize the predicted parameters. These were the best models for predicting resolution-related parameters. Although these models only work for resolution-related parameters, they are used to predict all parameters, as no significant difference is observed when a different model is fitted to predict non-resolution-related parameters. Also, five random images from the database were segmented and compared by the author to compare the models.

It seems that the firefly method separates the nearby vessels better and generally defines the edges of the vessels better. The comparison between different models for extracting image features shows a significant difference in segmentation, although the presented model seems to provide better results in edge detection in the presence of noise and central vessels.

- ***Edge Tracking***

The tracking of the edges of the vessel and measuring their diameter was done using the bankhead method, which was presented by the researchers using the implementation in MATLAB software before this study. In this method, the different segments of the tracked images are derived from the segmentation of the binary images, which are thinned by detecting connected points that work to draw individual segments. Then, the center line pixels in the thinned section are interpolated using lines. The interpolation method is used to create the smoothed vessel image. Then the edges of the images are selected from the center line in the vertical direction. The edge is created as a point with maximum slope around the center line.

- ***Neural network structure in retinal image processing***

A neural network must have at least two layers. These are input and output layers. The input layer has the same number of neurons/nodes as there are features in the feature vector. In this thesis, the data set has 10 nodes with an optional node, which also has an output layer including 2 nodes, which respectively outputs the probability of detecting the retinal image noise in the feature vector and the noiselessness of the image. Other layers are called hidden layers. Any number of hidden layers can exist and each of these layers can have a different number of nodes. There is much debate about the number of hidden layers to use, arguing that two-layer networks are sufficient for most studies, but other examples show that networks with 120 or even 1,000 layers are more effective for image classification, such as those used in resNet. . In this research, the width of the layers (number of nodes) is also discussed, but the general consensus is that it is better to keep the layers narrower. Narrower layers have a faster training time and their performance is comparable to much wider layers.

The activation function is applied to each node in the network. The activation function determines the output of a given node based on its inputs. The inputs of a node have the weight of their own nodes, these inputs are summarized and applied to the activation function, and the result is the output of that node, which in turn is the input of the nodes in the next layer. It works. Also, the unit function is a function in which the output is zero for negative inputs and one for positive inputs. This indicated whether a neuron in the brain was targeted or not. This works well for linear classification problems, which is also a linear classification in this study, but for non-linear problems.

There is no effect. Other activation functions output a range of values, usually between -1.1 or 0.1, but these values can be normalized to the required range.

Table 2 : It shows the number of data allocated for training and testing and validation.

Test		Train		Validation	
Extracted	No Extracted	Extracted	No Extracted	Extracted	No Extracted
5	4	12	11	4	4

A neural network is a multilayer classifier that has been used for retinal image classification in this thesis. This is because it can establish connections with previous layers. This classifier provides superior benefits compared to existing structures. A neural network is a collection of dense blocks that are sequentially related to sub-convolutional operations and the combination of related dense blocks. This approach allows us to build a deep neural network that can create extensive changes in classification. Therefore, this task faces two primary obstacles. First, recall in a neural network is not suitable for dealing with image sequences, as it was previously created for static data and leads to the creation of features from path data. These features have been applied to the input of the classifier. Also, these inputs can deal with sequential data. Therefore, to obtain the distinction of sequence data, it is used. Real sequence data has high dimensional and manufactured products that give poor results when entered into the neural network model. After the path data samples have been preprocessed, they are entered into neural network models. These models are DenseNet, VGG19, and ResNet. It is observed that VGG19, ResNet, MobileNet have training accuracy of one with very slight drops, while their testing accuracy is less than one. However, these models have high cross-validation accuracy compared to the training data. Since the training accuracy is close to 90%, the model is likely to be slightly overfitted. Figure 6 shows the accuracy of the neural network in detecting retinal vein extraction from registered retinal images.

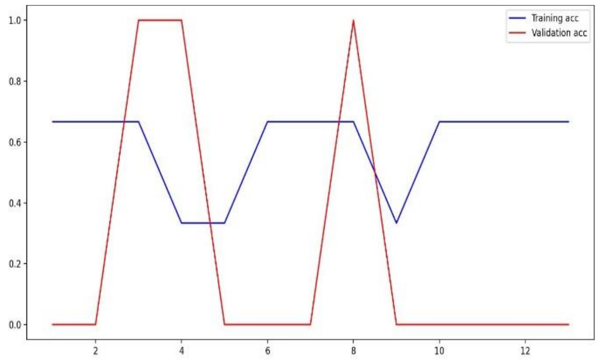

Fig 6 : The accuracy of the classifier in the division of blood vessels in retinal images.

Classification of retinal data is one of the most important stages in the data processing process. Various methods exist for the classification of retinal images, such as artificial neural networks (ANN), linear discriminant analysis (LDA), and support vector machines (SVM) that researchers use for the classification of data in extracting blood vessels from retinal images. In this thesis, a neural network (NN) is used for data classification. A neural network is a learning and training method inspired by the biological neural network of the body. The purpose of using a neural network in retinal data is to find and reduce errors in both analysis and statistical calculations. An artificial neural network has various layers and includes input and output layers as well as hidden layers and is well-known as a multi-layer perceptron. The number of hidden layers is chosen based on the complexity of the system in the input data and is selected as 10 in this thesis, as shown in Figure 7.

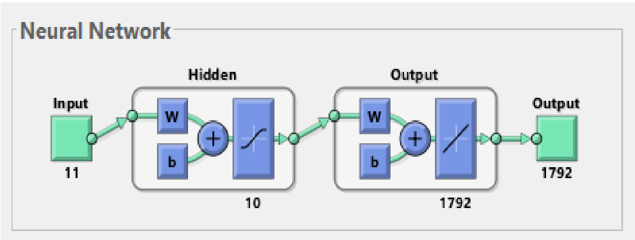

Fig 7 : The number of hidden layers of the neural network.

Neural network is a multi-layer classifier that is used in this thesis for classification. Because it can communicate with previous and current layers. This classifier offers superior advantages over existing structures. A neural network is a set of dense blocks that are sequentially connected by sub-convolutional operations and merging successive dense blocks. This development method allows us to build a deep neural network that can make many changes in classification.

Table 3 : Classification accuracy in extracting blood vessels from retinal images for training and testing and validation.

Train Accuracy	Test Accuracy	Validation Accuracy	Train Loss	Test Loss	Validation Loss
93.25%	89.74%	88.12%	0.06	0.15	0.08

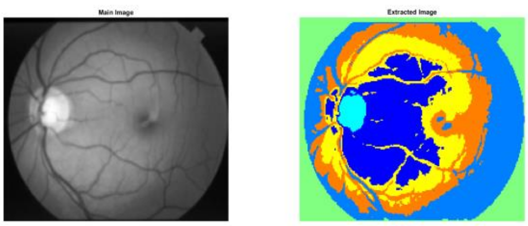

Fig 8: The image shows a sample of vessels extracted from the retina.

Conclusion

The proposed neural network-based vessel segmentation algorithm with the extraction of curvelet features as an effective approach to extract retinal vessels from retinal images. In comparison with reference [11], the accuracy of the proposed method in the DRIVE and STARE datasets improves slightly, with 93% and 94%, respectively. It has generally improved in sensitivity and specificity in both datasets compared with other algorithms. It performs better segmentation and has less error than existing methods, especially in details of the retinal image that contains most of the critical features for detection and identification. In addition, the receptive field has been enlarged, and the number of training parameters has decreased significantly, which indicates a great potential for significantly increasing the volume of identification data and shortening the detection time.

However, further research is still necessary to obtain more accurate features. More features of retinal images should be extracted under different conditions, different stages of diseases, or different healthy individuals. In addition, specific criteria are needed to evaluate quantitative details of segmentation. Continuing research provides stronger screening for retinal diseases through computer-aided detection and identification of the retina in the future.

Moreover, the network structure and the proposed construction method in this thesis have significant reference importance for many other applications. The network structure of the vessel extraction from retinal images effectively prevents inappropriate data from being learned, while reducing the number of training parameters. It has potential consequences for other applications of exploratory biological algorithms, not only limited to image processing problems.

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