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Blood Vessel Detection in the Retina Using Convolution Neural Network

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ABSTRACT

Modern-era developments in authentication systems have changed from traditional methods based on passwords or signatures to new methods based on biometric patterns. Biometric patterns are unique to each person, and identifying individuals has become much more accurate. Biometric cognition uses an intelligent method to identify a person with some unique characteristics of a human being. Unlike traditional methods, these biometric methods are more reliable and safer. Diagnosing blood patterns of retinal images is one of the safest ways to authenticate taking into consideration the monopoly nature of these patterns for each individual and their non-reproducibility and alteration. In the present study, the Convolutional Neural Network (CNN) was used to identify the pattern of blood vessels in the retina. DRIVE dataset was used to evaluate results. The images of the retina of different people were stored in this dataset. After extracting the patterns within the retinal layers for each person as a model indicating the identity of these individuals, the patterns related to the training and testing datasets were compared to determine the identity of individuals. Properly tested samples increase the accuracy of the proposed method, while incorrect detection will cause an error in the proposed method. The results showed that the average accuracy of matching blood vessel patterns for retinal images in the proposed method was 94.83%, which is high and comparable to previous methods.

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Introduction

Biometric recognition or biometric authentication refers to the automatic identification of a person based on anatomical (fingerprint and iris) or behavioral (signature) characteristics [1]. This identification method offers various advantages over traditional methods including identification cards (codes) or PIN numbers (passwords) [2]. First, the identified person x must be physically present at the identification point, and secondly, identifying x based on biometric techniques eliminates the need to remember the password or carry the token [3]. With the increasing integration of computers and the internet into everyday life, it is necessary to protect sensitive and personal data [4]. By replacing PINs (or using biometrics in addition to PINs), biometric techniques can prevent unauthorized access to ATMs, mobile phones, laptops, and computer networks. Unlike biometric attributes, PINs or passwords can be forgotten, and valid documents such as passports and driver's licenses can be forged, stolen, or lost. As a result, biometric systems can be useful for enhancing security and reducing financial fraud. The retina of the human eye is a thin tissue made up of nerve cells [5]. Because of the complex structure of retinal capillaries, each person's retina is unique. The retina of the eye has a pattern of blood vessels of the eye that is unique to each person and it is very difficult to change and reproduce it [6]. The patterns are different for the right and left eyes in the same person and the eyes of twins. Although any pattern of vessels usually remains stable throughout human life, it can change under the influence of certain diseases [7]. The retina of a person remains unique throughout a person's life and does not change over time. Retina detection technology determines the patterns of blood vessels using light entry methods. Irradiation of light to the blood vessels located in the thin nerve behind the eye causes pattern recognition vessels to occur in the retina [8]. Retina detection is used in very high-security environments (nuclear and weapons research sites, communication control facilities, and a very large transaction processing center) [9]. Convolutional Neural Networks (CNN) were used in this study to identify the pattern of blood vessels in the retina. CNNs are one of the most important deep learning methods in which several layers are trained in a powerful way [10]. These networks are among the most efficient methods in various applications of computer vision and deep learning [11]. In this study, the local features and the initial level of the images were extracted by a CNN, and then learning transpired in several existing layers. The details related to the images and the characteristics of the patterns in the image were learned well. Extracting image features using deep learning can achieve good results in matching the searched patterns in images [12]. In order to extract biometric features, a standard data set named Digital Retinal Images for Vessel Extraction (DRIVE) [13] was used. In this dataset, images related to the retina of different people were stored. Using CNNs, the vessels in the inner layer of the retina were extracted. The structure of these vessels is unique for each person, which makes it possible to recognize a person's identity. After extracting the vessels inside the retinal layers for each person as a pattern showing the identity of these people, a comparison of the patterns related to the training data and test data was carried out to determine the identity of the people. Correctly recognized test samples increase the accuracy of the proposed method. The present article divided into five sections. In the second section, various techniques and methods of blood vessel detection in the retina in recent years are reviewed. In the third section, a proposed method for blood vessel detection in the retina using CNN is discussed. In the fourth section, the results of the proposed method are presented. Finally, in the fifth section, the conclusion of the research findings and recommendations for future research are discussed.

Related works

This section reviews recent studies conducted in the field of blood vessel detection.

Roy et al. [14] investigated features based on vascular structure in the preparation of retinal digital patterns for retinal biometric identification. This required analyzing a large amount of data from various sources. They needed a faster and more robust automatic system to extract quantitative metrics from a large volume of retinal images. Therefore, fast and accurate detection of retinal features was chosen as an important element for biometric identification. In this study, a retina biometric key generation framework with a deep neural network was designed and implemented. The aim was to replace semi-automatic or automatic retinal vascular feature identification methods. This approach commenced with the segmentation of basic color images followed by the selection of some unique features such as the center of the optic disc, the center of the macula, and specific branching points in the deep neural network model. For better understanding, the key generation process was displayed with the help of GUI in the final stage. The training and testing of this network were carried out with the images of the DRIVE dataset. The obtained results demonstrated a 94.17% accuracy for this dataset.

Jin et al. [15] investigated the automatic segmentation of retinal vessels in the diagnosis of some diseases such as diabetes and hypertension. In this paper, a modified U-Net was proposed which took advantage of the local characteristics of retinal vessels with a U-shaped architecture. Deep Unet (DUnet), with sampling operators to increase output resolution, was designed to extract context information and enable accurate localization by combining low-level features with high-level features. In addition, DUNet considers retinal vessels in different shapes and scales by adaptively adjusting the fields according to the scale and shape. The accuracy output obtained for this model on the DRIVE dataset was 94.02%.

Tuba et al. [16] presented a new definition of the geometric features of retinal image shapes using a hierarchical matching structure. In this algorithm, the displayed retinal images are surrounded by blood vessel areas, which are called enclosed areas. A complete set of area-based features and boundary vessels are defined in the enclosed areas. In feature-based boundaries, by defining the corner points of the enclosed areas, new features such as the corner angle of the enclosed areas, the central distance, and the weighted corner angle are defined, which can well describe the amount of boundary changes and the geometry of the enclosed areas. The query is used to match the enclosed areas with the enclosed areas recorded in the database. It has also been used to filter the enclosed areas recorded in the database and reduce the search space from the features extracted in the hierarchical structure of more complex features. Finally, the candidate scenarios corresponding to the query of the enclosed areas are compared with the proposed decision scenario in order to identify or reject the query image. In this scenario, identification is performed when at least two bounded regions of the query match two bounded regions of the individual in the database. The proposed algorithm has been tested on standard retinal benchmark images from the DRIVE dataset. The obtained results illustrated a 93.82% accuracy for this dataset.

Wang et al. [17] proposed a new method based on retina image matching by SVM to identify people. Since a person's retinal vessels are a signature, that is, a distinct and unique pattern is identified from the person, this method works based on the image of retinal blood vessels. The proposed method in this paper consists of a multi-agent image registration and then a polygonal image re-registration. The main advantage of this two-step image registration method is that it is able to take into account both hard and non-hard deformations that naturally occur in retinal tissues. After this step, a step is defined to evaluate the decision recognition criterion, relying on a suitable normal function, to determine whether the pair of images belong to the same person or not. The proposed algorithm was tested on standard retinal benchmark images from the DRIVE dataset. The obtained results demonstrated a 92.67% accuracy for this dataset.

Proposed method

CNNS are able to simultaneously extract local features and feature weights from an image without the need for pre-processing. These networks basically integrate low, medium, and high-level features in a continuous multi-layer mode, and the feature levels can be enhanced by the number of depth layers. The structure of CNN is generally composed of convolutional alternating layers and sub-layers for sampling in addition to fully connected layers and SoftMax layers. Although the

CNN architecture has the advantage of not requiring a feature extraction process before use, CNN training is very time-consuming and difficult as it requires a very large labeled dataset to construct and train before the model is ready for classification. Note that this dataset might not always be available. In addition, there are hardware requirements to process a large number of filters for larger image sizes. Recent evidence shows that the depth of the network is critical. This research presents the image classification approach using convolutional neural networks with a random sampling approach. The proposed method details will be presented in the rest of this section.

In the present research, with the purpose of identity authentication, the detection of blood vessels in the retina was carried out using CNN. The proposed CNN has several hidden training layers, and each of these layers has its own activation functions with different applications. The general goal of each of these layers is to train on the images and propagate the results to the next layer in order to improve the training. Therefore, the term deep learning is usually used for CNNs. In the layers of the proposed CNN, the characteristics that determine the boundaries of the image and indicate the differences between the components in the images are determined. In order to implement the proposed method in this research, the standard dataset of digital retinal images for vessel extraction DRIVE dataset was used. The images in the training dataset were presented as input to the proposed CNN model and simulated using MATLAB software. The CNN used in this research consisted of several convolutional layers, pooling layers, fully connected layers and a SoftMax layer. In the proposed method, the middle layer of the CNN has a convolutional layer, which is the most elementary layer in the middle-hidden layers. The function of this layer is to extract important features in each image and assign each feature to a neuron. Therefore, the number of neurons in this stage is determined based on the characteristics of the images. Then, according to the importance of each feature in determining the vessel pattern in the image, the neurons are weighted in this layer. The input images to this layer have a size of 768 * 584. In order to manipulate the pixels, a size change is made in the beginning and each image is converted into a 512*418*1 row matrix. The extracted features will have smaller dimensions than in the original image. In the next layer, which is a max pooling layer, the selected and weighted neurons from the previous layer are entered. In this layer, 4*4 square pixels are used, which are reduced to 2*2 square pixels after applying max pooling, almost halving the size of the images at this stage. 2*2 square pixels represent the highest values in 4*4 square pixels. The weight of the neurons also change according to the changes applied to the pixels and features. Finally, the output of this layer is transferred into a SoftMax layer to determine which features are most important in this layer for ascertaining the pattern of blood vessels in the retina. This action is repeated in the network and the amount of data becomes smaller and smaller to determine the best features for ascertaining the pattern. The output layer in the proposed CNN includes nodes that show the weight of each image feature in order to assign it to the final patterns of retinal vessels. The number of pixels in the output layer is not necessarily equal to the number of input pixels, and only the pixels that have a large role in determining the pattern are obtained as output from the proposed CNN. The characteristics of the layers of the proposed CNN are shown in Table 1.

Table 1. Proposed Convolutional Neural Network Architecture.

Laye Name	Kernel Size
Input Layer	768*584
Convolution Layer	512*215
Convolution Layer	256*256
Convolution Layer	256*256
Pooling Layer	128*128
Convolution Layer	256*256
Pooling Layer	64*64
SoftMax Layer	32*32
SoftMax Layer	16*16
Fully Connected Layer	16*16
Output Layer	4*4

The convolution layer is a set of kernels with the size n × n × c, which is able to process small parts of the inputs. This method is able to increase the accuracy in identifying the changes made in the images and small differences in the spatial positions of different pixels related to different areas of objects, which can lead to faster detection. The output layer is fully connected to the outputs of the last integration layer and a class label is considered for each output unit. Moreover, weight sharing is an important rule because it is able to reduce the number of trainable parameters. As mentioned, the standard DRIVE was used in this research. The proposed method divides the images of this dataset into two parts, training and testing. The training dataset is used to learn the model. In addition, the test dataset is used to evaluate the proposed method.

Input layer: This layer extracts the images related to the training dataset from the original dataset and delivers them as input to the proposed CNN.

Convolutional Layer: This layer extracts the features related to the input training images and transfers them to the middle layers as training parameters. This layer acts as a feature extractor and is trained by the basic features of the input images. Neurons in convolutional layers are divided into feature maps. In this layer, each neuron is responsible for mapping to a feature and determining specific values for that feature. The influence of each feature in determining the class of the training image can be based on a set of adjusted weights. The weights of the current neurons are transferred to the corresponding neurons in the next layers.

Pooling Layer: In the proposed convolutional neural network, after the convolutional layer, the Max Pooling layer is used to extract the most effective neurons and features from the image. By using this layer, the amount of data in the middle layer is reduced. In addition, by reducing the spatial resolution distance, this layer enables feature mapping and thus achieves spatial invariance for the input data. In general, the purpose of using the max pooling layer in the proposed method is to transfer the maximum value in a receiving field to the next layer.

Fully Connected Layer: In these layers, each of the features extracted from the image is considered a parameter, and in this layer, a weight is determined for each of these features according to its class label. In fact, in this layer, the effect coefficient of each feature is specified for each person, and the proposed model is trained based on these coefficients. Convolution and pooling layers are usually stacked on top of each other in order to identify important features of an image as it moves through the network. Fully connected layers interpret these properties and perform functions on them with high-level arguments. These layers are completely connected with each other in order to determine the coefficients of each of the features so that in case of violations and errors, the entire middle layer is aware of this error.

SoftMax Layer: For classification problems, the use of the SoftMax function at the end of a convolutional neural network is known as a standard method. The SoftMax function sets the outputs of each class between 0 and 1 and divides them based on the number of outputs. Consequently, it is possible that the entry is in a certain class. It should also be noted that the amount of computation in fully connected layers is usually a significant challenge due to the computation-to-data ratio. In this section, a global compression layer whose output is a simple linear bundle input can be used as an alternative. At the end of this layer, in order to classify in the convolutional neural network, the necessary learning is done on training images, and these images are stored in an image dictionary according to the person's characteristics. This dictionary is the effect coefficients of each person's image characteristics, which are stored for later comparisons.

Output Layer: This layer uses the output of the previous layer and compares the test images with the previous images in the data bank and states whether or not the image matches. In this layer, the matching rate of the characteristics of the test image is compared with the ratio of the characteristics of the training images, and the matching percentage of each test image with the training images is determined. The highest matching percentage indicates the authentication of the desired person. If this matching cost is less than a threshold value, an error based on the absence of a person's image in the data bank will be declared.

Experimental results

DataSet

As previously mentioned, in the proposed method, to extract the biometric features of retinal blood vessel patterns, the DRIVE standard dataset was used. The DRIVE database was created to enable comparative studies of blood vessel segmentation in retinal images. This dataset included information on the division of retinal vessels, specifying the morphological characteristics of retinal blood vessels such as length, width, height, angles, and branching patterns used for diagnosis, screening, and treatment. Furthermore, in this dataset, retinal maps and branch point extraction were used to record the temporary or multi-mode image and square pixels (2*2 or 3*3) of the retinal image. In addition, the retinal vascular tree was unique for each individual and could be used for biometric identification. Images from the DRIVE database were obtained from a diabetic retinopathy screening program in the Netherlands. The studied community included 1000 people between the ages of 25 and 90. Each image was stored as a compressed JPEG file in the dataset for use in further research work. All images were captured using a 3CCD Canon CR5 camera with a 45° field of view. Out of the 1000 images used in this database, 600 were training images and 400 were test images. For training images, a single manual segmentation of vessels was available. For the test images, there were two segments, one of which was used as an automatic standard, and the other could be used to compare the computer-generated segments with those of an independent human observer. Moreover, a mask image was available for each retinal image that represented the region of interest. The proposed CNN model extracted the patterns of blood vessels in the images based on the opinions of ophthalmologists and features in the image. Next, by comparing the class labels of each of the training images, the features of the images were trained for the purpose of authentication. Therefore, the proposed CNN determined a specific pattern for each class of the training data set. When the test images were entered into the model, the proposed model predicted the desired class for each of the test images according to the pattern determined for each class in the training phase. If the prediction of the model matches the real class of the images, the classification and prediction of the model will be correct and the accuracy of the proposed model will increase. In the proposed method, the data set was divided into three parts: training, validation and testing. The number of training data was considered equal to 600 images, of which 400 images were used for training, 100 images for validation, and 100 images for testing. The validation part was used for measuring the performance of the model against the training data. The remaining 400 images in the original dataset were used as the final test images for authentication. Figure 1 shows an example of input images.

Figure 1. An example of an input image.

Simulation environment

The proposed method was implemented using MATLAB programming language version 2019 in a Windows environment and by a standard computer with Intel(R) Core(TM) i7-5500U CPU@2.40GHz, Nvidia GeForce GTX 1660 Ti graphics card with 1536 cores, and 8GB RAM.

The training stage

The proposed CNN used in the present study included three main layers: input, middle, and output. As shown in Figure 2, images were received as input, and training was applied to them. The weight values of the classes in the middle layers were checked based on the training function and the cost function, and weight was transferred to the next layer for each feature. Finally, the weight value for each of the pixels that played a decisive role in the pattern of retinal vessels was sent from the middle layer to the output layer. By applying these weights to the values of the attributes, the patterns related to the input images were obtained if the results applied to the specified threshold. It can be stated that if the results of multiplying the weights in the attribute values of a sample were more for each of the pixels, the desired pixel would be extracted as a pixel on the pattern of retinal vessels.

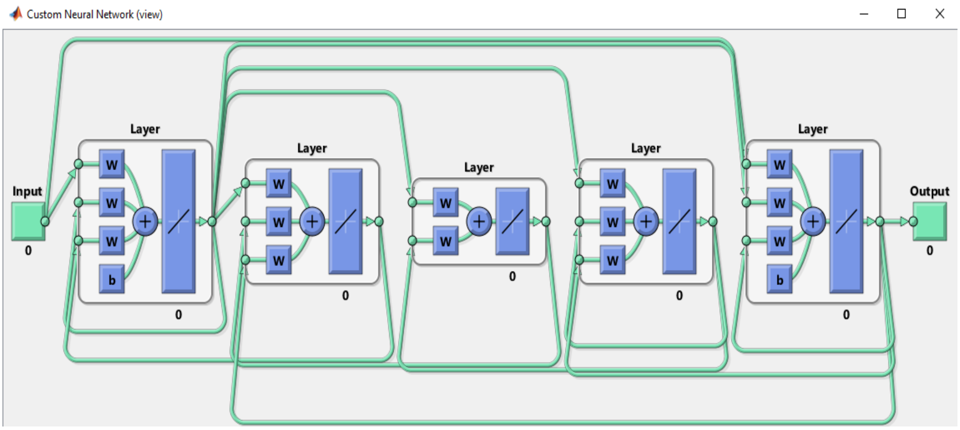

Figure 2. Training of the proposed CNN.

The testing stage

After training the proposed model on the training images and creating patterns for each class, the test images were entered into the model to check the compatibility of the patterns extracted from the training images with the patterns related to retinal blood vessels in the test images. By extracting the weights related to the test images and matching them with training patterns, the proposed model matched the patterns related to retinal blood vessels in two categories of training and test images. Figure 3 shows an example of the output test images labeled by the proposed model.

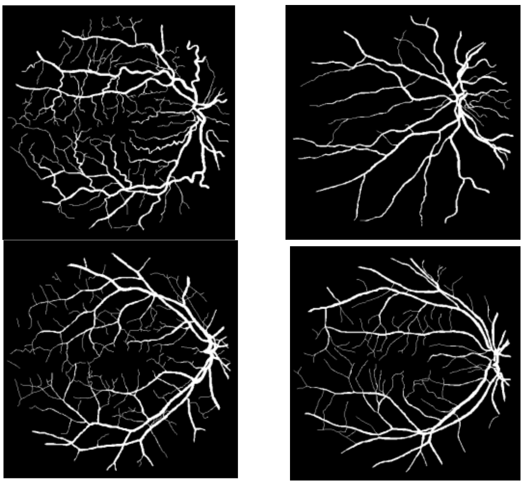

Figure 3. Examples of the output test images labeled by the proposed model.

Evaluation Criteria

The evaluation criterion used to measure the accuracy of the proposed model in this research was the correct matching rate of blood vessel patterns in retinal images in the stages of model training on the three sets of training, validation, and testing images. For this purpose, a confusion matrix was drawn, in which the number of correctly matched images versus wrongly matched images in the training, validation, and data testing stages was determined. This matrix contained four true positive (TP), false positive (FP), true negative (TN) and false negative (FN) elements, which are defined in the proposed method as below:

- **TP:** The patterns of test images and training images are the same and the model correctly recognized the same.
- **TN:** The patterns of the test images and the training images are the same and the model incorrectly detected a mismatch.
- **FP:** The patterns of the test and training images are not the same, and the model has correctly detected the mismatch.
- **FN:** The patterns of the test and training images are not the same, and the model mistakenly recognized the same.

By extracting the parameters of the confusion matrix, evaluation criteria can be obtained based on the confusion matrix in order to compare the results of the proposed model with the patterns of blood vessels in real retinal images provided by expert doctors. The most important of these criteria are Accuracy, Precision, Recall, and F-measure. These criteria are defined based on the following relationships.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

$$\text{F} - \text{measure} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \tag{4}$$

Outputs of the proposed method

The evaluation criteria introduced in the previous section were used as a tool to measure the quality of the proposed method and compare it with other existing methods. If the proposed model performed well on the validation of images, it can be guaranteed that the model can perform well on the test images as well as the next unknown images that will be referred to the model. Figure 4 shows the performance of the developed model for training, validation, and test images.

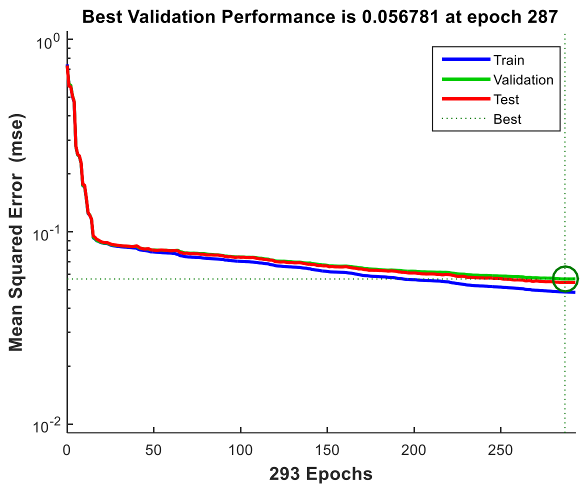

Figure 4. Performance of the proposed model for training and validation and testing images.

The graph in Figure 4 has four lines. The dotted line represents the best performance in each iteration, the blue line represents the performance of the developed model for training images, the green line denotes the performance of the developed model for validation images, and the red line denotes the performance of the developed model for test images. As can be observed, the dotted line is aligned with the green line, meaning that the performance of the proposed model for the validation images is the best, and the line corresponding to the performance of the model for the training and test images is the corresponding line which is close to the performance of the model for the validation images and it indicates the optimal performance of the developed model. The matching of the three lines with the dotted line in the proposed method occurred in epoch 293. Figure 4 illustrates that the performance of the proposed model for training and test images is almost the same. The next criterion used to measure the accuracy of the proposed model in this study was the amount of error in the model training stages on the training and test images in the model repetition stages. When the input images are directed to the intermediate layer, the intermediate nodes assign weight to these images and based on this weight create the training function. Then, this function is applied to the images to determine the number of images that are correctly classified. The number of wrongly classified images is considered as training error in that iteration. The lower the value of this error, the more accurate the classification of the model and the higher the accuracy of the proposed model. Figure 5 presents the error frequency graph.

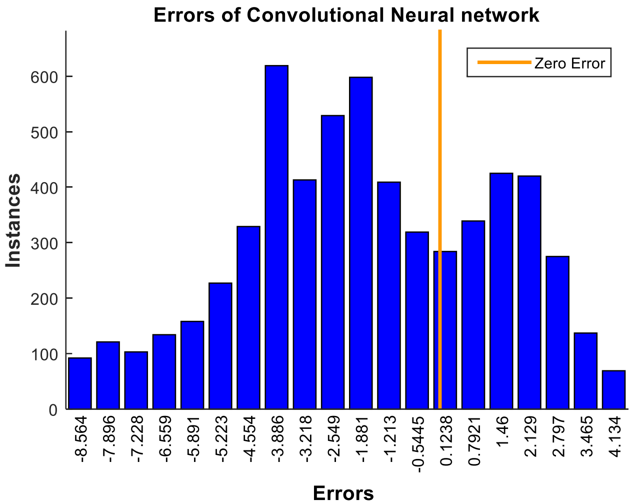

Figure 5. The error frequency graph.

Figure 6 shows the confusion matrix related to the proposed method.

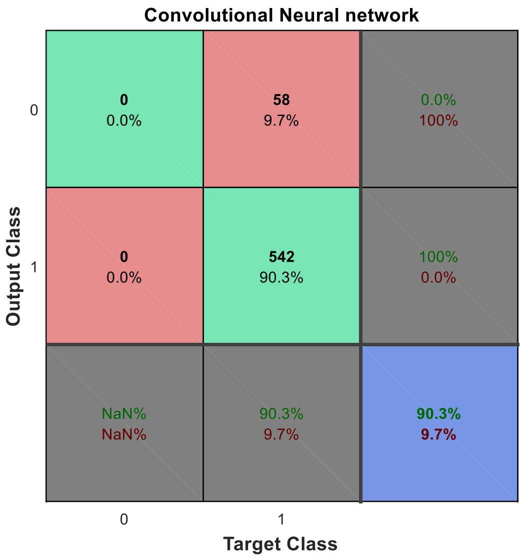

Figure 6. Confusion matrix of the proposed method.

As shown in Figure 6, in the proposed method, 90% of all blood vessel patterns in retinal images in the dataset, which includes training, validation, and test images, were correctly classified. Table 2 shows the comparison of the values related to the evaluation criteria in the proposed method.

Table 2. Evaluation criteria values.

Evaluation Criteria	Values
Accuracy	94/83 %
Precision	99/72 %
Recall	90/05 %
F-Measure	94/64 %

As shown in the table above, the proposed method performs well in terms of the evaluation criteria. The high accuracy of the proposed method shows the high ability of this method in training the model based on the characteristics of training images of retinal patterns and matching blood vessel patterns in these images with test images. Figure 7 shows the Accuracy diagram, Figure 8 shows the Precision diagram, Figure 9 shows the Recall diagram, and Figure 10 shows the F-Measure diagram.

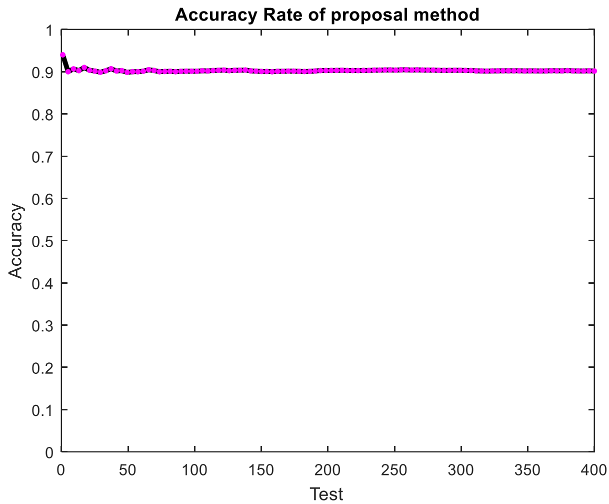

Figure 7. Accuracy diagram of the proposed model.

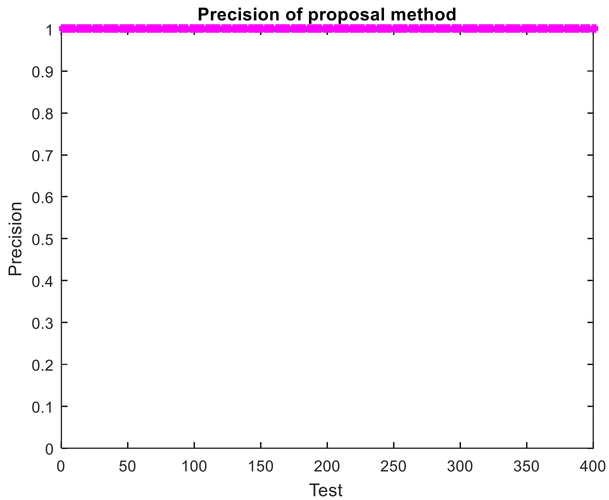

Figure 8. Precision diagram of the proposed model.

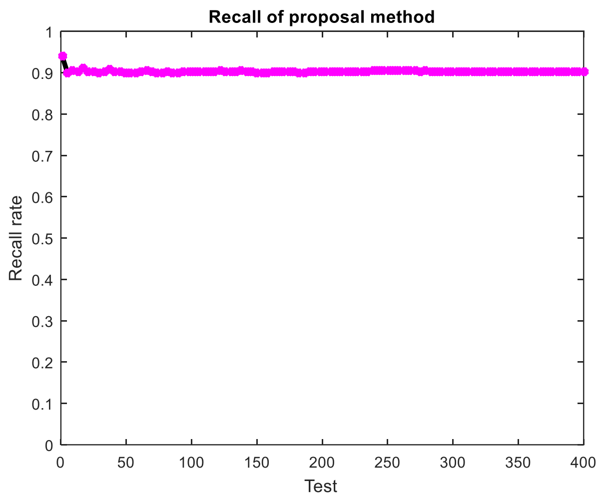

Figure 9. F-measure diagram of the proposed model.

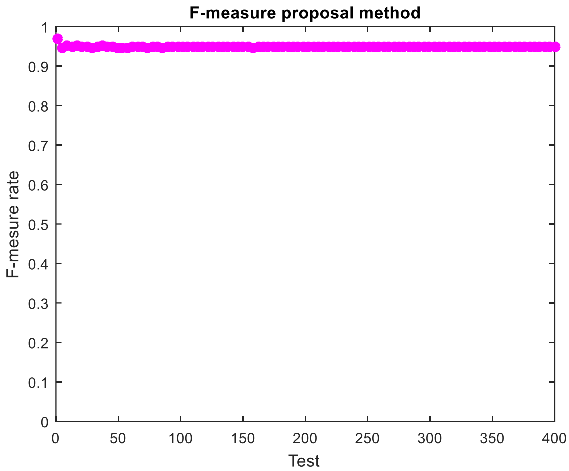

Figure 10. F-measure diagram of the proposed model.

As shown in the above diagrams, the proposed method performed optimally in terms of the introduced evaluation criteria. After evaluation, to measure the performance validity of the proposed method, the accuracy obtained for the proposed model was compared with the previous methods mentioned in section 2. As can be observed in Table 3, the performance accuracy of the proposed method on the DRIVE dataset is more optimal than other methods with regard to the volume of training images.

Table 3. Comparison of the accuracy of the proposed model with previous methods.

Method	Accuracy
[14]	94/17%
[15]	94/02 %
[16]	93/82 %
[17]	92/67 %
[#]	94/83 %

Conclusion and future works

Authentication technology plays an important role in security systems. To protect data stored on each consumer device, traditional methods mainly use passwords or personal identification numbers. Although these methods are easy to implement, passwords and personal identification numbers are easily forgotten. Biometric recognition uses an intelligent method to identify a person with some unique characteristics of a human being. Therefore, biometric authentication is a method in which a person can be uniquely identified by assessing biological characteristics. Biometric recognition refers to the automatic identification of a person based on anatomical features (such as fingerprints and iris) or behavioral features (such as signatures). The retina of the eye has blood vessel patterns unique to each person and it is very difficult to change and reproduce it. Even the patterns for the right and left eyes in the same person and the eyes of twins are distinct. The retina of a person remains unique throughout that person's life and does not change over time. In this research, to identify the pattern of blood vessels in the retina, CNN was used. Convolutional neural networks are one of the most important deep learning methods in which several layers are trained powerfully. This method is very efficient and is one of the most common methods in various computer vision applications. In this research, a CNN extracted the features of the images by deep learning the local features and the initial level of the images. Since in the convolutional neural network method learning takes place in several existing layers, the details of the images and the features of the patterns in the image are well learned. Therefore, extracting the features of images using deep learning can achieve good results in matching the searched patterns in the images. The results of the tests show that the average accuracy of matching blood vessel patterns for retinal images in the proposed method is 94.83%, which is high and comparable to previous methods. Considering the importance of authentication using biometric systems, the proposed method can be used in future research by increasing the convolutional and pooling layers in the CNN to reduce the volume and error of training and extracting important features. It can also be used in future research by using meta-heuristic methods as activation functions in pattern extraction layers and by using reinforcement learning to train the features in the image.

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