A Finger Vein Pattern Recognition System Using ROI Extraction and Convolution Neural Network

Dnyaneshwari P.Wagh[1], Fadewar H.S[2], Shinde G. N[3]

School of Computational Sciences, SRTMU, Nanded, Maharashtra, India[1,2], Yeshwant Mahavidyalaya, Nanded, Maharashtra, India[3]

Corresponding author: Dnyaneshwari P.Wagh, Email: dnyaneshwari.wagh15@gmail.com

Biometric identification technology has advantages over above traditional method, since each person's biological characteristic is unique and difficult to counterfeit. At present finger vein recognition is an ideal identification technology. The finger vein pattern in extracted from the input database images, the extracted vein patter in treated as the Region of Interest (ROI) image. This image is given as input to the Convolution Neural Network (CNN) for training. The CNN model extracts featured form the input image and trained the model. The trained model can then be used from recognition of new images. Three fingers per person have been used in the experiments and the proposed method produced good results in recognizing the person. The proposed model produced an accuracy of 100 percent during the testing phase.

Keywords:Finger vein recognition, Convolution neural network, Biometrics, Data acquisition, Vessel identification.

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1 Introduction

Today, traditional and ancient methods of system security information [1] are no longer usable as much as it is used by someone. They are two ways: The first method is based on the password or PIN that a person configures and knows, method which is not really guaranteed because the user can be forgotten by the password set by itself or by accident may be the same as another nobody. The second method is based on what the person has as a badge or chip card, but it is also not very reassuring due to deterioration, loss or of the theft of the emblem. So, these are two ways that are not 100% successful and are at risk. The need to developing another effective and safe way was overcome, as were the problems of recruitment and weakness. This method depends on the material information of the person and not on the information that she owns or knows. This method is used to identify individuals and is known as biometrics [2].

Biometrics identifies the "measurement of living things" and in a very broad quantitative study of living beings [3]. The argument for biometrics can be summed up as: Convenience: Passwords like credit cards, debit cards, cards identity or keys can be forgotten, lost, stolen and copied. In addition, today everyone must remember a multitude of passwords and have in their possession a large number of cards. For its part, biometrics would be immune to this kind of more badly that it would be simple and practical, because there are no more cards or passwords to hold back. Biometrics [4] would be able to reduce, without eliminating it, crime and terrorism because, at the very least, it makes life difficult for criminals and terrorists**.** The biological characteristics are classified into two types: physiological characteristics and behavioral characteristics. Physiological features include finger vein, palm, iris. Behavior characteristics include signature, speech, and gait.

At present finger vein recognition [5] is an ideal identification technology. This technology has the following advantages: (1) Each person's finger vein is unique, i.e., every human being has a different finger vein. (2) Each person's finger vein is quite fixed. It will not change throughout a human being's life. (3) A person's finger vein is easy to be sampled. (4) The template used in the identification system is not the original finger vein image but the feature of the image. Thus, the storage and transmission can be minimized.

The veins of the hand are of the network vary from person to person. Analysis of this difference helps to maintain points for differentiating one person to another.

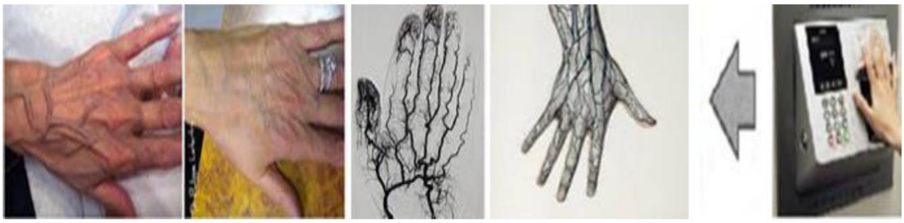


Fig. 1. Veins of the hand

Most of traditional finger vein identification systems [6] use a template in the form of bare data to store the finger vein information. Thus, the entire finger vein recognition system is likely to be completely exposed to the hacker attacks, which will make the biometric templates unsafe when it needs to store and transmit. This paper presents a finger vein pattern based person recognition system using deep learning technique. Section 2 presents the literature survey. Section 3 presents the proposed methodology. Section 4 presents the experimental results followed by conclusion and references.

2 Literature Survey

Miura et al., [7] has used the Line Tracking method which is one of the significant methods for finger-vein extraction. The finger veins can view as darker in the image and similar to the valleys in the infrared image due to the light-absorbing characteristic in this method. Based on the random finding of a pixel in the valley, the LT technique has implemented and the pixels have tracked in addition to the valley. It validates whether the cross-section s-p-t is orthogonal to the pixel centre to estimate whether a pixel is on a valley (being a part of the finger vein) and a valley is formed in intensity values. If incase the pixel is not on a valley, the 'valley pixels' have monitored by the method and randomly it is restarted another position for finger-veins tracking. How many times a pixel has tracked is listed out in the locus table which shows the output results and the finger-vein is captured in the infrared image.

Miura et al., [8] proposes a technique using the local maximum curvatures determination in the vein image's cross-sectional profiles. Based on the maximum curvature, the veins' center positions have extracted in this technique and have connected to each other for obtaining the final image.

Hu [9] has proposed the first moment invariants to recognize image patterns and image analysis. Recently, one of the popular methods is image moments for extracting the features. For image registration, pattern recognition, and compression, different kinds of moment descriptors have used. Moments have utilized if the image global properties are considered as vital points.

Yang et al. [10] has considered utilizing the phalangeal joint width as a soft biometric parameter for improving the accuracy of recognition for finger vein. More crucial issues are not solved although some valuable works are there in the recognition of finger vein. For example, the large-scale applications like the high quality image acquisition, and the high recognition rate.

Yanagawa et al. [11] has proved the human finger vein patterns diversity on 2, 024 fingers of 506 persons, but the medical proofs are not sufficient. It couldn't estimate how the recognition rate will be and the reliability of classification result in large scale applications. It has also considered whether the finger vein can use in judiciary like face and fingerprint. Additionally, the medical evidence regarding the finger vein stability is not sufficient. The enrolled template of finger vein effectiveness is the relevant issue in practical applications. It refers to that whether it's required to replace the enrolled template for every 5 or 6 years. The pattern of finger vein impacting is uncertain when the diseases occur in the surrounding environment.

Dai et al. [12] has developed the captured image quality at certain extent by using the non-uniform intensity infrared light for finger vein image. The recognition of finger vein will promote hugely by using the device with high performance and lower price.

Zhang et al. [13] has introduced a system of automated finger-vein verification based on the mean curvature which is at a point on a surface and the surface curvatures mean in all directions. In this method, the pattern of vein can view as valley-like structures based on the consideration of image's intensity sur face as a geometric object. The shape of U or V has formed by a cross-section of valley-like structure means a long channel as a gutter. However, its inversion refers to the ridge-like structure. In a valley-like structure, the set of points have determined that are included the negative mean curvature. To estimate the valley-likeliness or the ridge degree, the mean curvature has implemented in other applications.

Lee et al. [14] has improved a system of reliable and robust palm vein identification based on the device of a low-cost NIR CCD camera-based palm vein for real-time personal identification through the palm vein images capturing. For extracting the features, a rectangle area (ROI) is extracted from a palm vein image using a preprocessing algorithm. The utilization of 2-D Gabor filter is extended for representing a low-resolution palm vein image based on its texture feature and a normalized hamming distance is applied for matching different images of palm veins. A new method proposes known as the directional coding for coding the features of palm vein in the representation of two bits. The biometric features have represented in the format of bit string in this technique and convenient storage and speedy matching have enabled. The palm vein feature's total size reduces to 2520 bits in this representation.

3 Proposed System

Finger vein recognition is a biometric authentication method which uses pattern recognition techniques based on pattern images of finger veins below the surface of the skin. Recognition of fingers in the veins is one of the many forms of biometrics used to identify individuals and verify their identity.

The system consists of four stages: acquisition, preprocessing, extraction of characteristics, and classification.

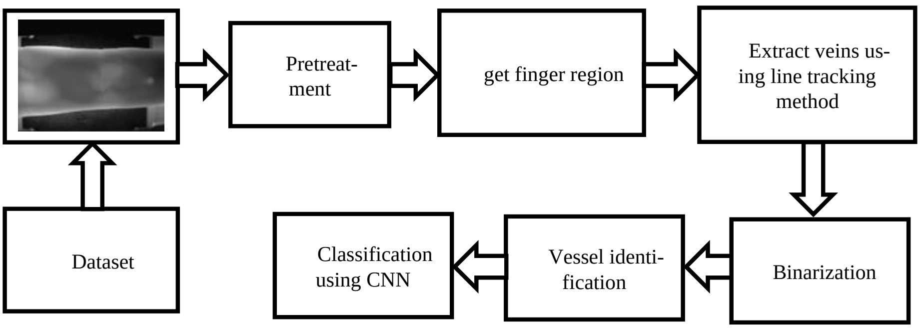


Fig. 2. Block diagram of a biometric identification system

Data acquisition: This phase collects the biometric data of people clients. Several industrial processes can be used for acquisition such as apparatus Photo, reader footprints digital, etc.

The biometric reader consists of a system that emits infrared light and a sensor retrieving a reflected image:

(i) The biometric reader emits infrared light.
(ii) Blood loaded with oxygen has the characteristic of absorbing waves close to infrared.

(iii) The biometric sensor retrieves a reflected image representing the mapping of veins of the fingers.
(iv) The power of the biometric reader is to perform measurements between different intersections of the veins.
(v) From the measurements, it searches for the identity of the person in its database local.
(vi) Depending on the pre-programmed time access authorizations, the reader activates the opening of the access.

Pretreatment: Before the feature extraction step, the data from the sensor device image must be preprocessed. The purpose of image preprocessing is to provide robust Region of Interest (ROI) image for feature extraction. The good ones performance of a finger vein image depends on the quality of the vein image on point.

ROI Extraction: This most important step is extracting the return on investment. In the finger vein images, there are unwanted regions (image background) and the area value (finger area) in the image. The value area is called ROI, and the ROI extraction is the processing to locate and extract the finger area of the captured image and to remove the background from the image.

Feature extraction: Extracting features is one of the most crucial and most important steps important aspects of the Finger Vein Recognition (FVR). During this step, the quantifiable property of the biometric trait base is created, called a model, which is useful in identifying the individual. For example, in a biometric fingerprint system, the position and orientation of thoroughness points in a fingerprint image are the key element that must be different from someone else's. An efficient technique for extracting characteristics is a step that improves the accuracy of vein recognition of fingers. The vessel pattern on the finger image is extracted in all directions and thereby all the vessels are extracted along the flow. The entire process is described in the algorithm below:

Algorithm
Step 1: Prepare dataset
Step 2:Pre-process the dataset(resizing)
Step 3: Get finger regions
Step 4: Extract veins using repeated line tracking method
Step 5: Binarize finger vein image
Step 6: Vessel identification
Step 7: Classification using CNN

Convolutional Neural Networks (CNN): Convolutional Neural Network (CNN) is as shown in figure 3. It is a multi-layered neural network with a structure. The input layer and the output layer are the first and last, respectively correspond to the floor. Adjacent to the input layer, convolution layer and multiple pooling layers can be placed in pairs, followed by several composed of a fully-connected layer.

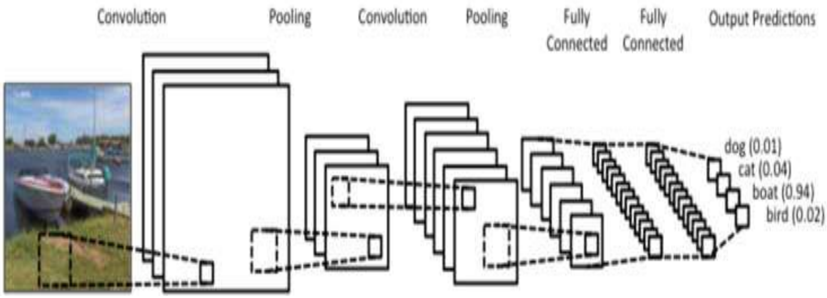


Fig. 3. Example of convolutional neural network

The convolutional neural network is a methodology specialized in image analysis among artificial neural networks. The convolution layer in figure 3is close to the previous layer (input layer or previous pooling layer).It is a structure in which nodes in the next layer are connected to the nodes in the next layer. It serves to extract features of a specific local area. The pooling layer is the previous convolution. It plays a role of integrating the abstracted values of a specific area part of the layer node.

A. Convolutional layer

Convolution is one of the operations frequently used in image processing. Input an image *f(x),* an image corresponding to the mask *g(x)* when called, following operations *f(x)*g(x)* is called convolution, as shown in figure 4.

$$f(x) * g(x) = \int_{t=-\infty}^{\infty} f(t)g(x-t)dx$$

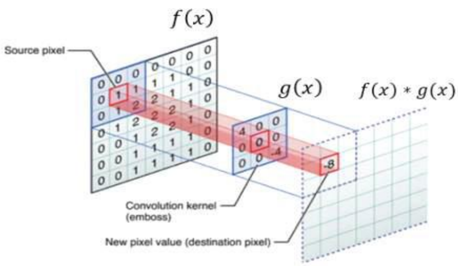


Fig. 4. Convolution operation

This image convolution process is expressed as a 3×3 matrix in the example. The convolution filter moves the image and multiplies and sums each pixel value and it goes on.

In the convolution operation, let the size of the input image *f* be $W_1 \times H_1 \times D_1$, and As a result, when the size of the image corresponding to *f*g* is $W_2 \times H_2 \times D_2$, The relationship is as shown in figure 5. Here, *K,F,S,P* is called 'hyper parameter', This is a value that CNN users should select appropriately for their application field.

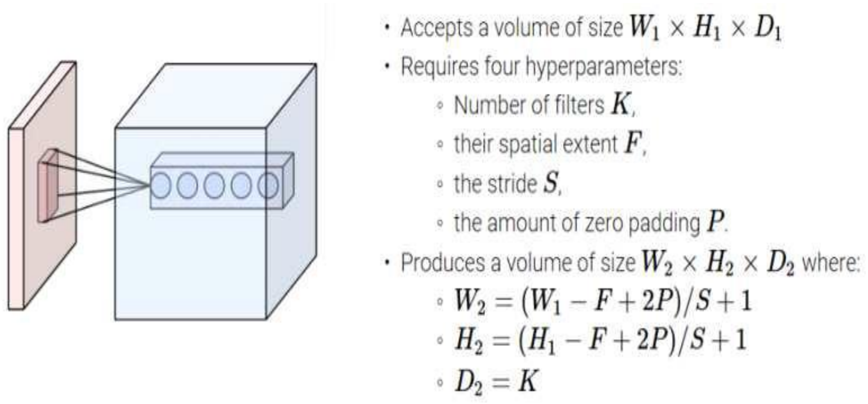


Fig. 5. Input and output of convolution operation

Figure 6 shows a 3×3×2 image by applying convolution to a 5×5×3 image. Two filters of 3×3 size were used here. Input of the picture in the blue area of the volume is the convolution target area, and the filter is Filter, Output Volume represents the output value. Blue target area as input and the filter is scanned one by one from the top to the bottom from the left column, and the filter value is multiplied by a matrix. After calculating and reflecting the bias value and passing the value to the next layer, the same operation is performed. Repeat in the next layer to produce the final result.

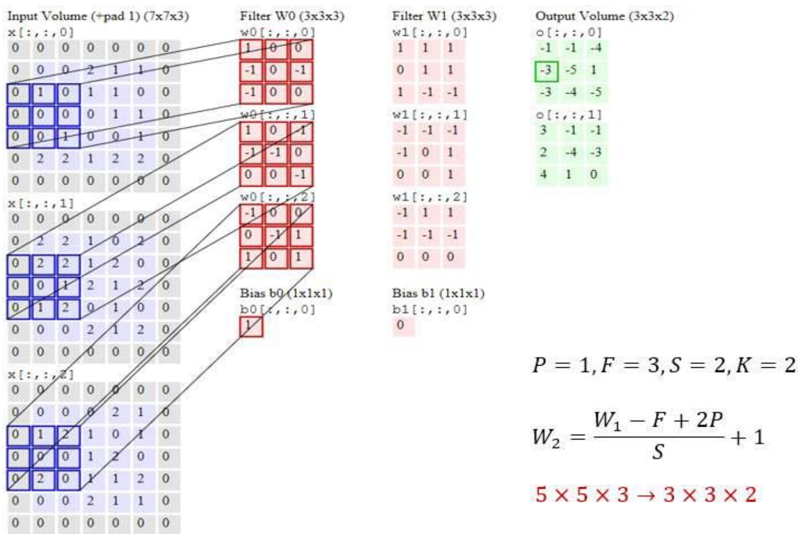


Fig. 6. Example of convolution application

B. Pooling layer

The pooling layer plays a role in reducing the size of an image by a down-sampling method. The most used method for configuring the pooling layer is to use a 2×2 size window. There are average pooling and max pooling. The pooling layer has important dimension is reduced by leaving only information, and a specific value among the values sampled in 2×2 size. Extract one and convert it into a 2×2 result again. In this process, the average value if find it, it is average pooling, and if find the maximum value, it is max pooling. In the case of Max Pooling there is an advantage of giving a value that does not change even if the image is moved in parallel. Figure 7 shows an example of max pooling using a 2×2 window. It can see that the width and height of the image are reduced by half by pooling.

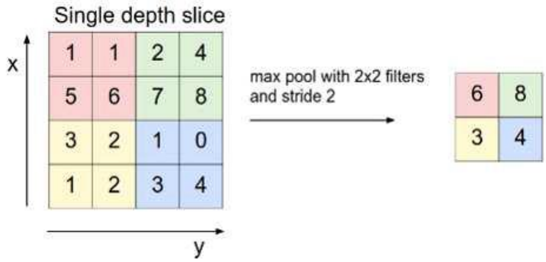


Fig.7. Example of Max pooling

In the pooling operation, the size of the input image *f* is called $W_1 \times H_1 \times D_1$, and the result of pooling is the size of the corresponding image is $W_2 \times H_2 \times D_2$, the relationship between these two images is as follows: It is as shown in figure 8.

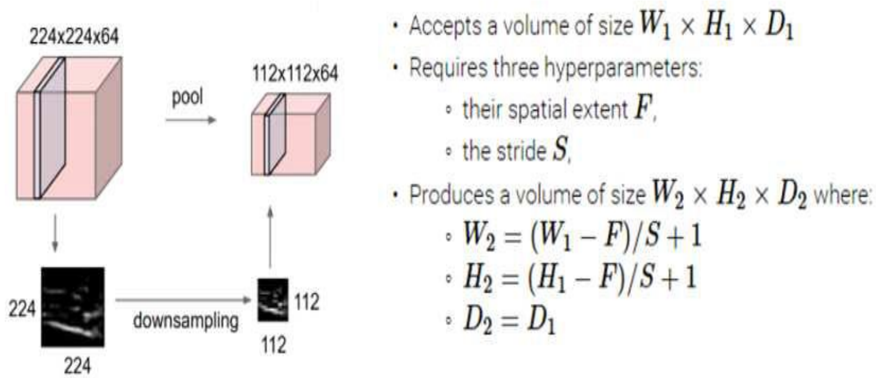


Fig. 8. Input and output of pooling operation

C. FC layer learning

Due to the structure of CNN, the FC layer is located last. Therefore, the weight when learning, the update is performed first. The calculation of the FC layer's forward direction is as shown in figure 9.The process of obtaining the total input value at the node and calculating the output value through the activation function.

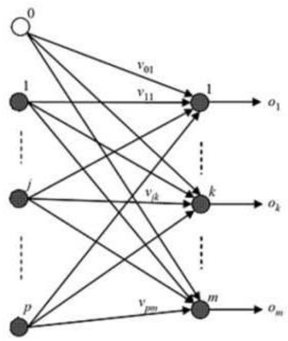


Fig. 9. Forward Calculation at FC Layer

The error back propagation for the recursive calculation of the delta term in the FC layer is as follows: Of course, the value of the delta (δ) term in the output layer is the error observed at that node. It is calculated separately on a basis.

Finally, the update of the weight existing in the FC layer is as follows, Error backpropagation at the FC layer is shown in figure 10.

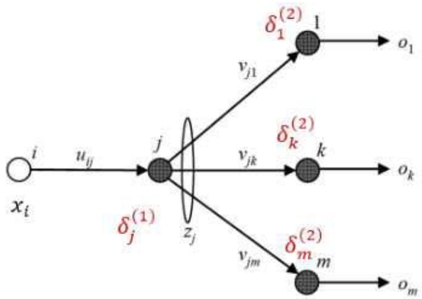
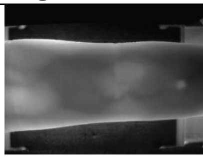
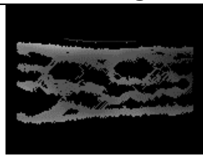
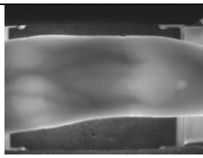
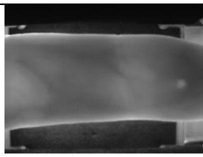
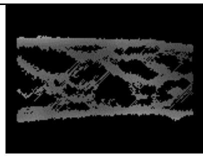
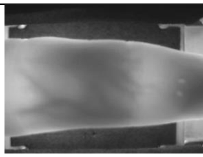
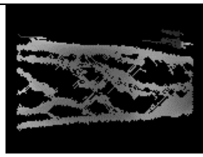
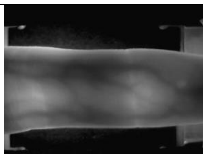
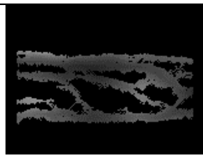


Fig. 10. Error back propagation in FC layer

4 Results and Discussion

Table 1 shows the input images with their Region of Interest images. The dataset has total of 60 images with 10 persons each of 6 images.

Table 1: Input finger vein image with ROI

Person	Finger Vein	Identified finger vein
1		
2		
3		
4		
5		

When train networks for deep learning, it is often useful to monitor the training progress. Specify 'training-progress' as the 'Plots' value in training Options and start network training, train Network creates a figure and displays training metrics at each iteration. Each iteration is an estimation of the gradient and an update of the network parameters. The figure plots the following:

- Training accuracy — Classification accuracy on each individual mini-batch.
- Smoothed training accuracy — smoothed training accuracy, obtained by applying a smoothing algorithm to the training accuracy. It is less noisy than the unsmoothed accuracy, making it easier to spot trends.
- Validation accuracy — Classification accuracy on the entire validation set (specified using training Options).
- Training loss, smoothed training loss, and validation loss — The loss on each mini-batch, its smoothed version, and the loss on the validation set, respectively. If the final layer of network is a classification Layer, then the loss function is the cross entropy loss.

Figure 11 shows the training accuracy plot of CNN network.

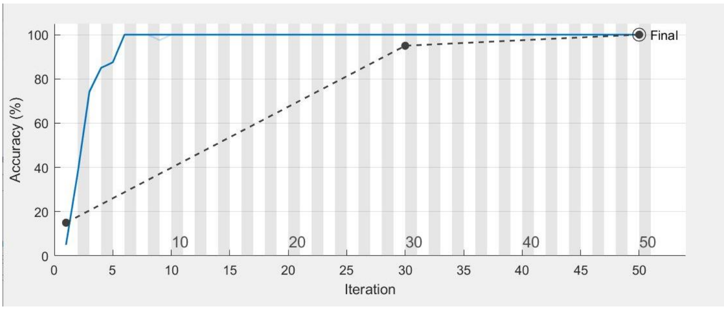


Fig. 11. Training Accuracy graph

Figure 12 represents the training loss plot.

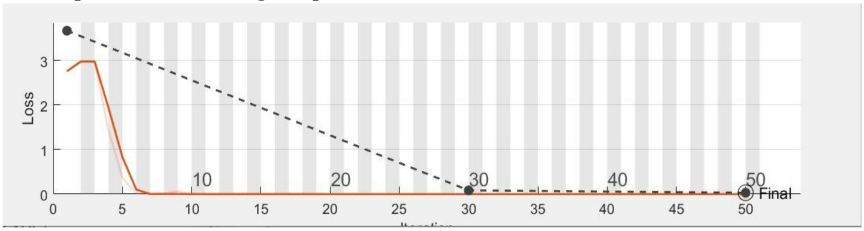


Fig. 12. Training loss plot

Training processing

Table 2: Confusion matrix - training

Actual class / Predicted class	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
Class 1	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Class 2	0.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Class 3	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Class 4	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0
Class 5	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0
Class 6	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0
Class 7	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0
Class 8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0
Class 9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0
Class 10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0

Table 3: Parameters

Actual class / Parameters	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
TP	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0
FP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
FN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
TN	36.0	36.0	36.0	36.0	36.0	36.0	36.0	3.0	36.0	36.0
Precision	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Sensitivity	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Specificity	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Model Accuracy	1.00									

A Confusion matrix is an N x N matrix used for evaluating the performance of a classification model, where N is the number of target classes. The matrix compares the actual target values with those predicted by the machine learning model. This gives us a holistic view of how well our classification model is performing and what kinds of errors it is making. The figure 13 represents the confusion matrix of 10 classes.

Testing

Table 4:

Actual class / Parameters	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
TP	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
FP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
FN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
TN	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0
Precision	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Sensitivity	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Specificity	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Model Accuracy	1.00									

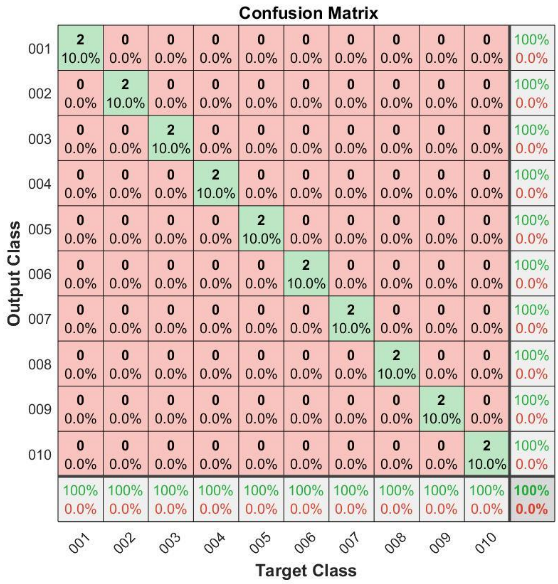


Fig. 13. Confusion matrix

5 Conclusion

Biometrics identifies the "measurement of living things" and in a very broad quantitative study of living beings. The argument for biometrics can be summed up as: Convenience: Passwords like credit cards, debit cards, identity cards or keys can be forgotten, lost, stolen and copied. The proposed model consists of two phases. The ROI extraction phase and the CNN based recognition phase, The ROI extracted images are sent to the CNN model for recognition. The testing phase provided that the proposed method recognized the persons in the database accurately with 100% accuracy.

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