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# Matching Minutiae Fingerprint Q-Learning Approach for Detail Coordination: Identifiable Mark Point

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***Abstract***

*The use of fingerprints for high-precision recognition and identification of people is one of the most reliable biometric symbols because it is non-invasive. In this paper, we propose an innovative approach to detect details on low contrast resolution image quality of fingerprint images. Existing algorithms are not very susceptible to sound and image excellence due to the lack of level of intensity. We recommend a reliable route to find fingerprints and then they can employ machine learning techniques to enhance image quality and choose the best course of action. For a sizable portion of the state, multi-layer concepts and intensive learning techniques are used before choosing the proper reward structure and research area for understanding the distribution of rewards. It is of great importance that the opportunities for the development of the content are easy and educational activities are of great importance. Experimental outcomes test indicates that the best way to extract Q-Learning details is to use a contemporary finger recognition system framework, which offers extremely viable or even significantly better results may generate than several cutting-edge techniques in terms of AROC, accuracy, and other metrics.*

**Keywords:** Machine learning, minutiae extraction, convolution neutral network (CNN), support vector machine (SVM), principal component analysis (PCA), deep learning (DL)

## INTRODUCTION

At present, fingerprint-based systems can identify us based on our individual traits and characteristics. Behavioral or physiological characteristics can be present in these traits. For the time being, when we think of identification, we immediately think of biometric authentication or identification. Generally, involves observing and identifying each person's distinctive traits. These traits could include things like gestures, iris movements, voice, or even fingerprints. The recognition of fingerprints has grown to be an extremely common approach for authentication using biometric data due to its distinct features, broad category, and consistency [1]. A repository of blueprint fingers must be consulted to find a biometric authentication procedure or verification blueprint that resembles every aspect of the input fingerprints. The biometric use of finger samples can be significantly enhanced by the development of fingerprint samples. Deep learning (DL)–based research is being done to enhance performance on difficult hidden finger samples. To improve the biometric domain's dependability and efficiency, convolution neural networks (CNNs) can even be trained directly. As a result, DL enables the synchronization of data area improvements and feature extraction.

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As a physical characteristic of the body, fingerprint patterns are used through various objects' surfaces. Following that, the data used to identify fingerprints is typically divided into three levels [2]. Macros details at level 1 [1], that is, pattern, include ridge flow and pattern type. The Galton characteristics, also known as minute points, include bifurcations and endings. This is level 2 that is, points. A ridge's dimensional characteristics are included in level 3. By contrasting two fingerprints, they can determine how difficult systematic separation is and how strong as shown in Figure 1.

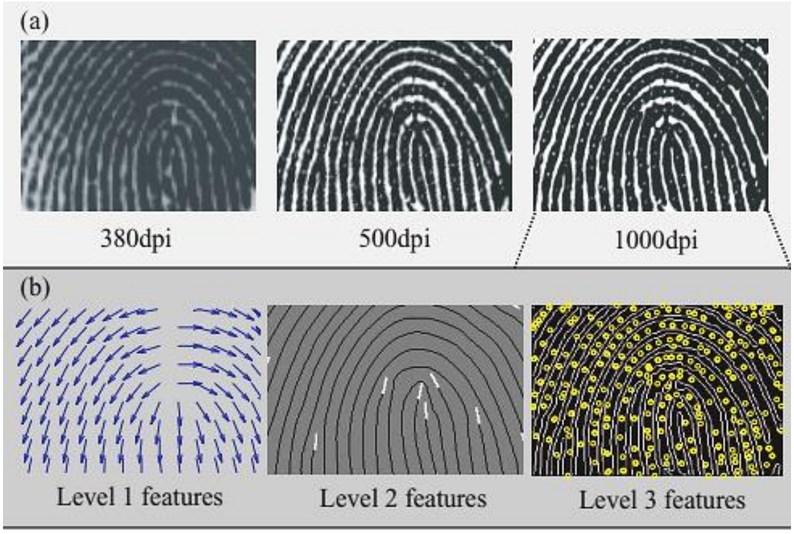



**Figure 1.** Fingerprint features extracted at different levels.

Even when the image quality is inadequate, it is still possible to retrieve the global ridge flow pattern because it is a clearly defined pattern. The entire image of dataset is reduced to just one template subset after the level-1 pattern group has been successfully resolved, which significantly cuts down on computation time [1] for a pair of prints.

Local ridge characteristics known as level-2 features or minutiae give each matching template a distinctive pattern. Although the idea of fingerprint exceptionality has generally been accepted, proper scientific validation is still lacking. Discusses the uniqueness of human fingerprints [3] determined by level-2 features, as well as the potential of indiscriminate fingerprint association.

Forensic investigators almost exclusively use level-3 features, or microscopic patterns based on scars, sweat pore spots, ridge patterns and additional incredibly minute features. The use of 1000 PPI (pixels per inch) resolution fingerprints for identification purposes by more and more biometric system vendors has recently led to the adoption of automatic computer system shutdown [4]. Systems for fingerprint authentication are used by infrastructure, businesses, and public institutions alike. However, most capturing systems are reliant on the surface of the finger, which can affect the accuracy of the identification (dust, temperature, humidity, etc.).

## MINUTIAE EXTRACTION SYSTEM

In the interim, several issues with the incorrect categories are to blame for the manual annotation. Since deep learning technology has advanced so quickly, it is now possible to learn the elements of discernment directly from the original picture without any image analysis. CNNs are used for the first time in [5, 6] to determine the spot of fingerprint images and then effect of the research is acceptable outcomes. The main concept of our paper is to provide the support vector machine (SVM) segment with the CNN-based study features to obtain segmentation results. Following the suggestion of the decision and incorporation of the regulation in this paper, other papers should create CNN using the principal components analysis (PCA) handle. Between each talk preparation and each integration preparation, the size of the learned indications is reduced by the PCA preparation. Furthermore, an additional benefit based on region of interest improvement execution on the effect of the invalid local point. After the over handle, the SVM component was used to distinguish between the advanced semantic features of distinctive thumb impression images and the eliminated semantic characteristics that were instinctively read to pre-recorded fingerprints. Following that, the category show is created using special mark preparation.

The neural network is useful for finding the unique characteristics corrected points from the existing template image as the next step. There are three layers in this neural network: input, hidden, and output as shown in Figure 2.

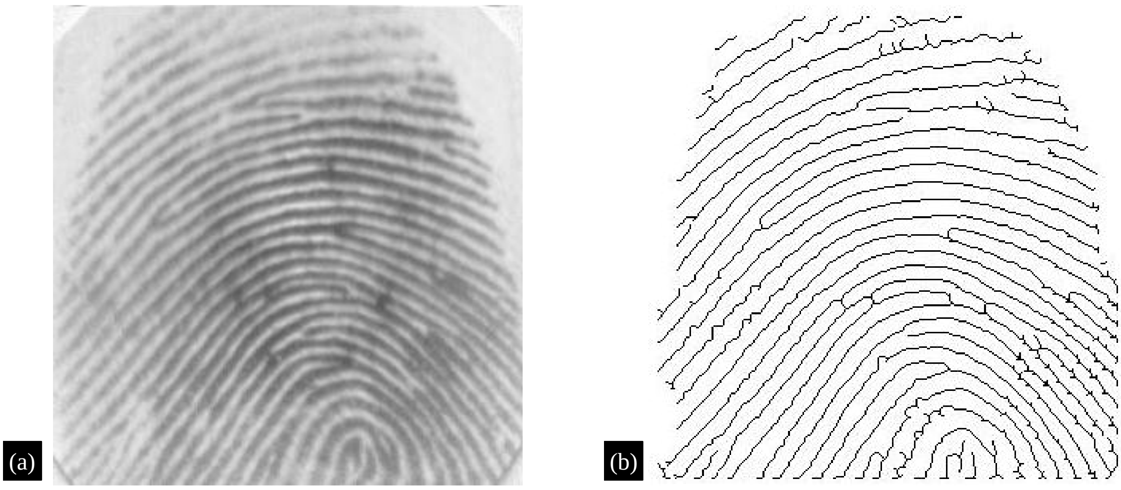


**Figure 2.** (a) Original fingerprint template. (b) After processed image.

- *The input layer:* The input layer, which is three-by-three-pixel blocks from the fingerprint image, has 9 neurons.
- *The hidden layer* is composed of three bifurcation and termination patterns in three-by-three configurations.
- A map with the same dimensions as the fingerprint image is the output layer. The map indicates non-minutiae points as 0, termination points as 1, and bifurcation points as 2.

## FINGERPRINTS MATCHING LAYERS

The relationship between two human fingerprints that have the specified interval number, that is, 0 to 1 is what this algorithm simply returns through fingerprints algorithms are the two main classes of finger algorithms [7]. Additionally, there are hybrid methods [8, 9] that combine them and are applied when the quality of the fingerprints is insufficient for comparison.

Convolution Neutral Network (CNN): A CNN, also called a hierarchical neural network, transforms a convolutional layer and a sub-sampling layer. The layers are as follows:
- Image processing layers.
- Max pooling layer.
- Classification layer.

### Image Processing Layer

Image processing layer is not necessary to redefine the set of filters that must be changed during the training process. More information can be made available in a system like edges or gradients if there is unexplained effort. The output layer makes things more visible.

Maps on each layer are the same size, measuring (Mx, My). The input image's proper location is used to transfer the kernel. The X and Y directories kernel skip pixels are determined by missing the spotted spaces between subsequent interactions.

### Max Pooling Layer

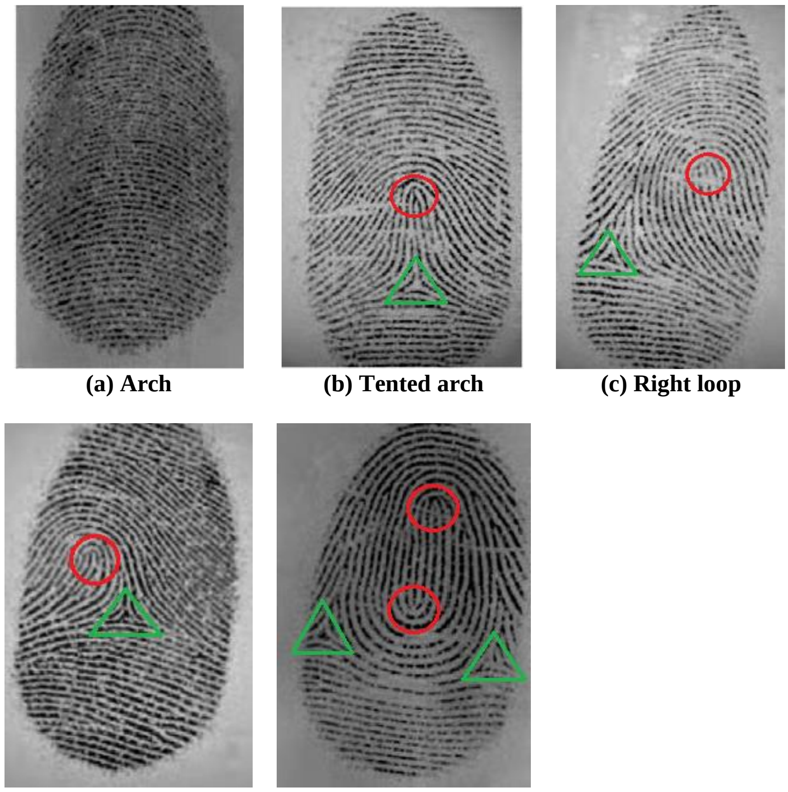
Distinction between the initialization and CNN is the employing from the upper level instead of the lower level. As an additional means of gathering or evaluation, the component listed below impacts pixels that are adjacent prior to assembly, they speed up assembly in this layer and choose consistent features that are better quality and become simpler. Multiple integrations allow for the acquisition of a position; add a fingerprint to images, with each component affecting a distinct direction.

### Classification Layer

The most significant layer concludes are either fully integrated into the corresponding layer of determination or the maximum pooling based on convolution on a vector of a 1-D element. A higher standard is linked to one value generated per category label.

## MATCHING TYPES OF FINGERPRINTS

Scientists classify fingerprints beforehand to lessen the computational demands of the fingerprint matching task. So, only a portion of the database of finger image data can be used for fingerprint identification. Only the first level features illustrate the overall direction of a fingerprint ridge flow that is utilized in fingerprint categorization [10]. The main use of second- and third-level features is fingerprint template matching because they are too specific and inconsistent. To better understand them, fingerprints patterns are divided into five main categories as given in Figure 3.



**(a) Arch** **(b) Tented arch** **(c) Right loop**

**(d) Left loop** **(e) Whorl**

**Figure 3.** Fingerprint patterns [11].

In the first-level feature, important points approximating the location of singular points and the orientation of the world ridge are described. Singular points are areas of a fingerprint with the most variation or a location where ridges unexpectedly shift fingerprints for access ridge flow movement. Core and delta types can be used to categories these singular points. It makes sense that ridge flows would congregate in cores and diverge into deltas.

- ***Arch:*** The only type of fingerprint that lacks a single point. Arch fingerprints have small ridges that move from one place to another.

- ***Right loop:*** The delta singular point is below and to the left of the core, and there is one core singular point. At least one ridge begins on the left side, travels to the center, then circles back to where it began.
- ***Left loop:*** It consists of a core and one delta singular point (the delta is to the core's right and below). At least one ridge starts on the right side, travels to the middle, then reverses direction and travels back to where it began.
- ***Tented arch:*** It contains one singular point in the delta (located below the core) and one central part. Arch flow is similar to ridge flow, but ridges have a stronger curvature.
- ***Whorl:*** A whorl consists of two delta and two core singular points. The complete turnaround is located at the center of one or more ridges.

## EXISTING ALGORITHM ANALYSIS

Zhang et al. [12] analyzed the mechanism of finger image rotation and its ability to affect key features (mainly details and singularities) of rotationally transformed fingers. It has been shown that the image transformation process can make a faithful record of the original fingerprint, which can sharpen change points and create false spots. Although they do not show image changes, quantization and interpolation processes have been shown to change the shape of the fingerprint. Their testing showed that as much as 7% of content could be inconsistent. Their position increases to 16px for matches. The angling position direction angle can be adjusted up to 90 degrees and up to 55 pixels.

Zhang et al. [13] went a step further to create a solution, namely using continuous images and two fingerprints, detail, and pore representative, and provided the Minimum resolution for pore removal, that is, anatomical evidence. They did the test on fingerprints at different resolutions (500 to 2000 dpi). Evaluating these solutions based on detail and porosity, their results show that they perform well on resolution 800 dpi.

A crucial first step in fingerprint recognition applications is fingerprint image enhancement, a method that makes the image clearer than it was originally [14]. The process of developing an algorithm for fingerprint recognition should be able to distinguish between ridges and valleys and connect false ridge points caused by insufficient load black (ridges). In any application-based recognition system, augmentation algorithms are a crucial step in addressing the noise on the fingerprint surface. Narrow streams appear white, and ridges appear black or dark gray. Weak skin, finger movements during recording or pickup, the sensors noise, and dry, wet, or oily fingers are the main causes of noise, glitches, and broken edges. Such method gives a preliminary process that creates ridges and valleys by working with the original image before providing detailed information.

According to Zhang et al. [15], most fingerprint matching techniques fall into two categories: general feature-based algorithms and detail-based algorithms. Because local details are less impacted by conflict, detail-based algorithms are frequently used in local knowledge perspective methods to generate multiple pairs of combining details of two fingers [15]. After filtering through a layer of Gabor filters that behave in various directions, the most widely used feature-based technique in the world also extracts long-range features of the area surrounding the reference point [15].

Given that removing fingerprints is an essential stage in defining automated fingerprint recognition system, it also plays a crucial role in the extraction procedure. The distinctive features of the fingerprint pore depend on the location and category of the fingerprint because despite the pores' simplicity, it is challenging to eliminate the substance of the pore with fingers. Recommended [16] is to solve this issue; pore energy transfer and deep CNN are used in a pore removal technique. Large fingerprints can be utilized to determine pore spaces on a deep mesh. They looked for local maxima to locate fingers with extraordinary endurance in fingerprint images to further enhance comprehension of the pores on the fingers. Finally, the test results indicate that fingerprinting aims to advance existing methods.

Here, the authors suggest a new method [17] and point out that CNNs are important in security measures to distinguish real fingerprint from artificial fingerprint. Using this CNN method, they make available an improved method for extracting and classifying tasks. Native binary format and extended output are used as well as names. Use this definition to determine the correct native binary format used to convert grayscale images to binary images use of the 3 × 3 matrix model. Details find gaps and differences in the reduction process. The local binary pattern and details are then combined using a fusion algorithm.

First, the ratio of available small parts, using a different histogram transformation equation called differential order histogram transform equation (contrast limited adaptive histogram equalization or CLAHE) and a grouping of Gabor filter [18] and fast Fourier transform methods. Next, the evolution of the fingerprint is determined by selecting small data from some local area of interest i.e., minutiae features. The thinned binary image is subjected to the SURF (speed-up robust features) and Harris detection algorithm combination to enhance detection outcomes. Experiment demonstrates the effectiveness and efficiency of the proposed system to achieve between 95% and 92.5% established authentication for FVC2002 DB1 and FVC2000 DB1s.

## PROPOSED Q-LEARNING STEPS

Here the authors find [19] a new geometric distortion difficulty in the fingerprinting process by proposing a fast and efficient distortion metric to avoid nonlinear fingerprinting. Although recently there are many schemes for detecting perturbations through unorthodox patterns based on experiment analysis, they think on deep convolutional neural network (DCNN) method to calculate key interference points between sample inputs as shown in Figures 4, 5, and 6. It has the following services:

- There is no need to guess the map of the event and progress on the respective fingers.
- Distortion parameters are calculated almost continuously for additional changes.
- Significant reduction in updating due to model changes in network logic.

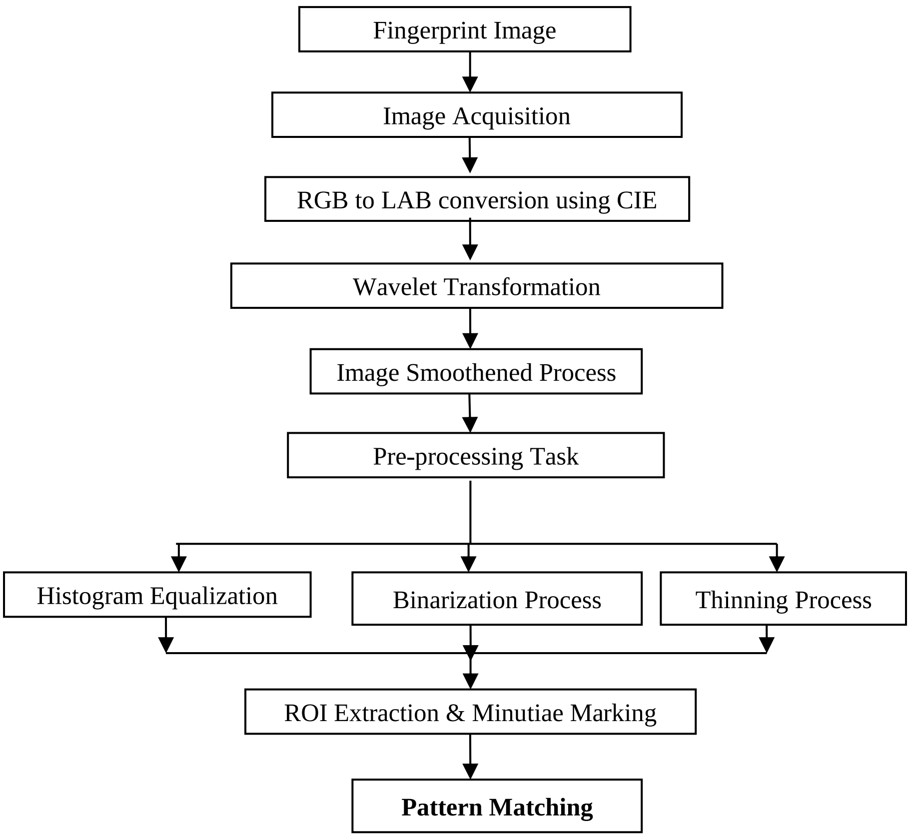



**Figure 4.** Workflow of matching minutiae fingerprint.

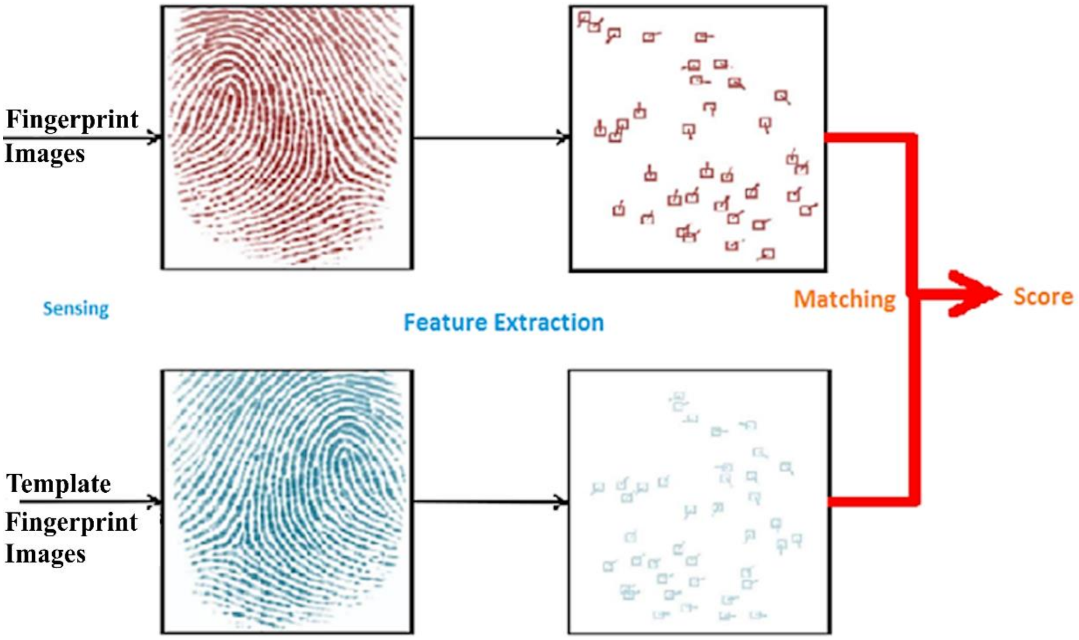



**Figure 5.** Matching fingerprint.

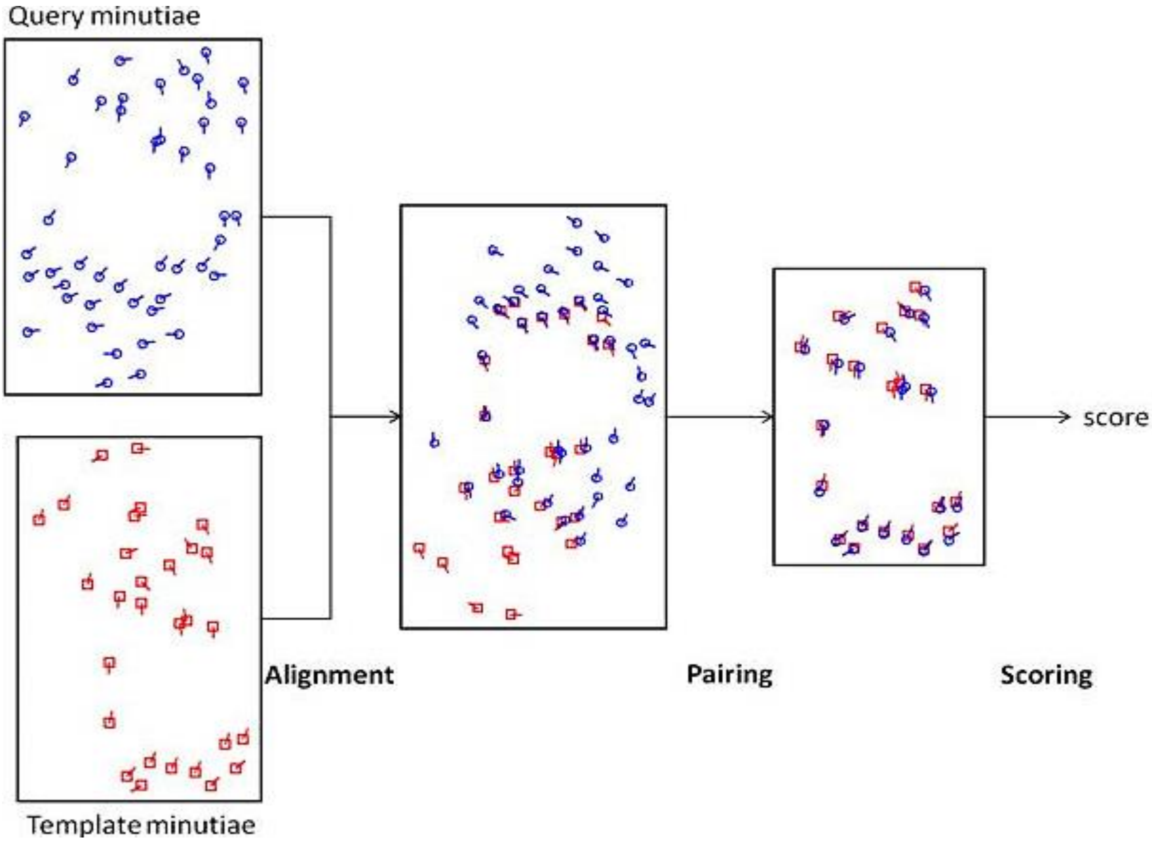



**Figure 6.** Proposed flow of Q-Learning method.

## PROPOSED ALGORITHM

### Calculation Steps

#### *Stage 1*

After preprocessing the template image with binarization and refinement, the adjusted pixels represent "1" or "0". Check the existing image pixel assessment by two methods:

- Initially, to select the pixel (P) = 1, then compute the key intersection number of the pixel (P) = 1 and draw the icon details.
- Second way, if the pixel value is "0", then the intersection is calculated over the pixel value with pixel value "0" or P = 0 and the minutiae point is marked. The cross-estimation calculation:

$$CN = 0.5 \sum_{i=1}^{\infty} |Pi - P\,i + 1|, \text{ with } p9 = p1$$

For the P pixel, Pi is the adjacent pixel value. Its eight neighbors are analyzed counterclockwise as follows in Table 1.

**Table 1.** Adjacent pixel value

| | | |
|---|---|---|
| P4 | P3 | P2 |
| P5 | P | P1 |
| P6 | P7 | P8 |

***Stage 2***

After the cross-estimation calculation of the pixel circle is considered, the registration of that pixel can be executed according to the property of the cross-estimation calculation value. Take the end point (EP) if CN = 1, and the bifurcation point (BP) if CN = 3. Other values of cross-estimation are not valid as shown in Table 2.

**Table 2.** Rules for crossing number (CN) selection

| CN | Property |
|---|---|
| 0 | Isolated point |
| 1 | Ending point |
| 2 | Connective point |
| 3 | Bifurcation point |
| 4 | Crossing point |

***Stage 3***

The next step is to extract precise details from the fingerprint image using the Q-Learning method. Input, hidden, and output layers make up this neural network.

- ***Input layer:*** A three-by-three adjacent pixel block from the existing fingerprint template through input layer contains 9 neurons.
- ***Hidden layer:*** The hidden layer has three-by-three separate and cut patterns.
- The map is the same size as the fingerprint. It has 0 indeterminate points, 1 intersecting point, and 2 disjoint points on the map.

Since there is only one loop in the training process, the neural network is taught offline. Some fork point rules disregard error points while there are well-known breakpoints:

- ***R-1:*** If the distance between the shot and the fork is significantly less than D1, then both points will be wrong. We need to eliminate these two elements.
- ***R-2:*** If the distance is less than D2, the two intersection points will be wrong. We need to eliminate these two elements.
- ***R-3:*** If the separation distance is less than D3 then small dots may be wrong.

We need to remove these two elements of minutiae points.

- Initialize the variables QL[i_image, o_image]
- read image,
- reduced the image to a single pixel value.
- Search for an image using three filters.

- centerm = one near center
- centbif = two Neighboring centers
- Reward calculation R = Euclidean distance (center, centbif)
- Swap rows in R
- Repeat this process (up to 8 adjacent neighboring pixels per result)
- go for initial position by permutation
- For this case, all R is small in non-small elements
- Replace non-small elements
- From the permutation step identify the input layer
- QL[i_ image, ot_ image]= Reinforcement [i_ image, o_ image] + $\gamma$*QL_max (o_ image)
- i_image = o_image
- Up to all 8 adjacent neighboring pixels as long as each instance
- end now

**Stage 4**

If the pixel is there, go to step 1, otherwise go back to details.

## PROPOSED ALGORITHM

### Algorithm Steps

***Input Data***

$MFPT_1$, $MFPT_2$, ..., $MFPT_n$ template fingerprints and MFPI fingerprint input specifications are fused.

***Output Data***

Recognized fingerprint.

- Separate the MFPI into L steps, that is, $MFPI_1$, $MFPI_2$, ……., $MFPI_N$; each step includes a unique feature set (N = 6 set).
- Set threshold values for contrasting at each level using histogram equalization.
- for i = 1 //N is the size of databases
- for j = 1: L do //L is hierarchical steps
- T1 = convert (MFPI, L) //Input fingerprint
- T2 = convert (MFPT (i), L) //Template fingerprint
- S (i) = MatchingScore(T1, T2) //Matching Score of Input and Template fingerprint
- if S (i) < Th //Score compare with threshold value
- break;
- else
- L= L+1; // Increase the Hierarchical step
- Repeat steps 5 and 6, then use step 7 to compute the matching score;
- if S (i) > Th then // Score compare with threshold Value ID = i; // Return Matched fingerprint
- return;
- end;
- end;
- end;
- end;;

## SIGNIFICANT OUTCOMES

Matching minutiae fingerprints has yielded significant outcomes in the field of forensic science. The utilization of minutiae fingerprint matching has led to the successful conviction of criminals and the exoneration of innocent individuals. Moreover, it has proven invaluable in solving cold cases and preventing future crimes as shown in Figures 7, 8, and 9.

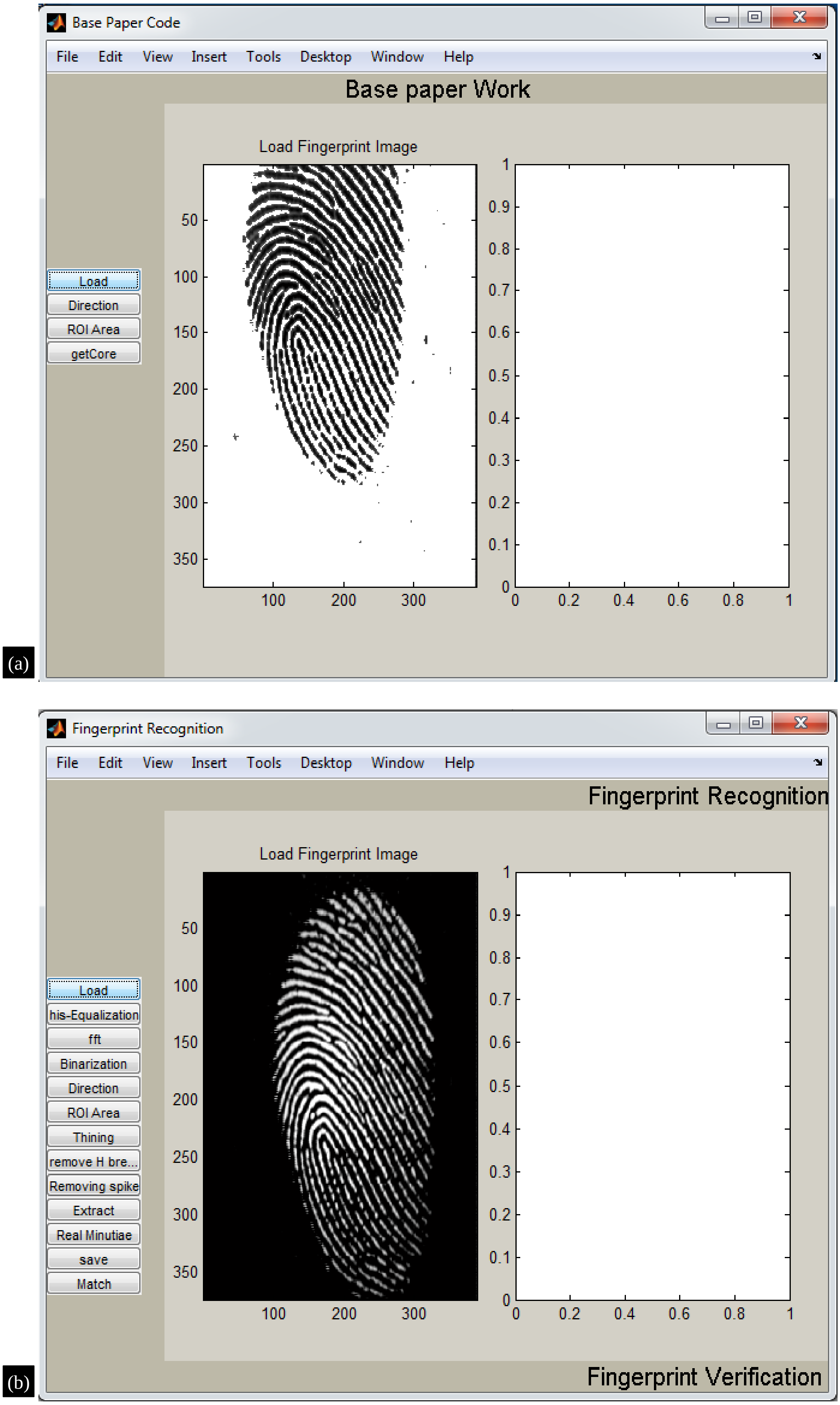



**Figure 7.** Fingerprint verification.

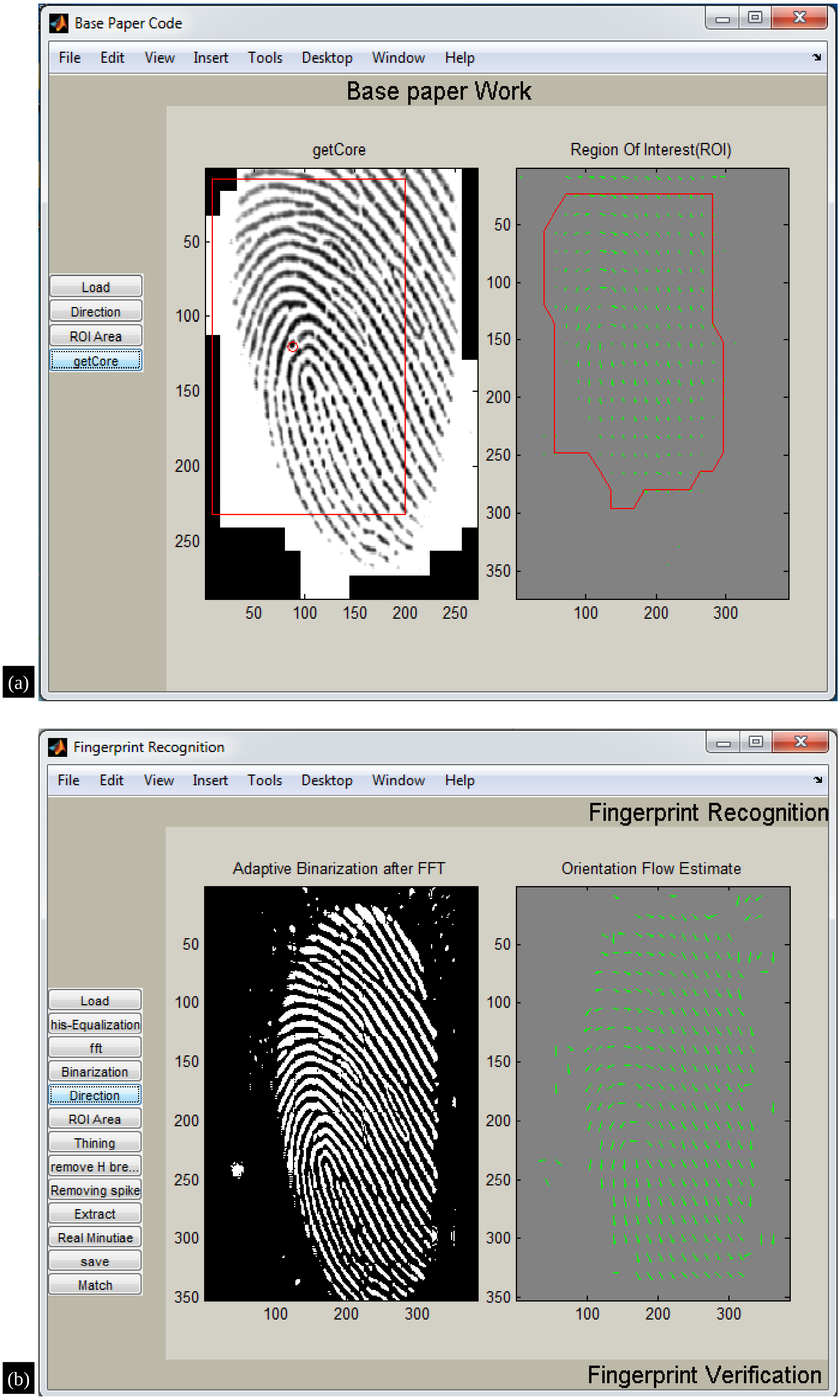



**Figure 8.** Fingerprint recognition.

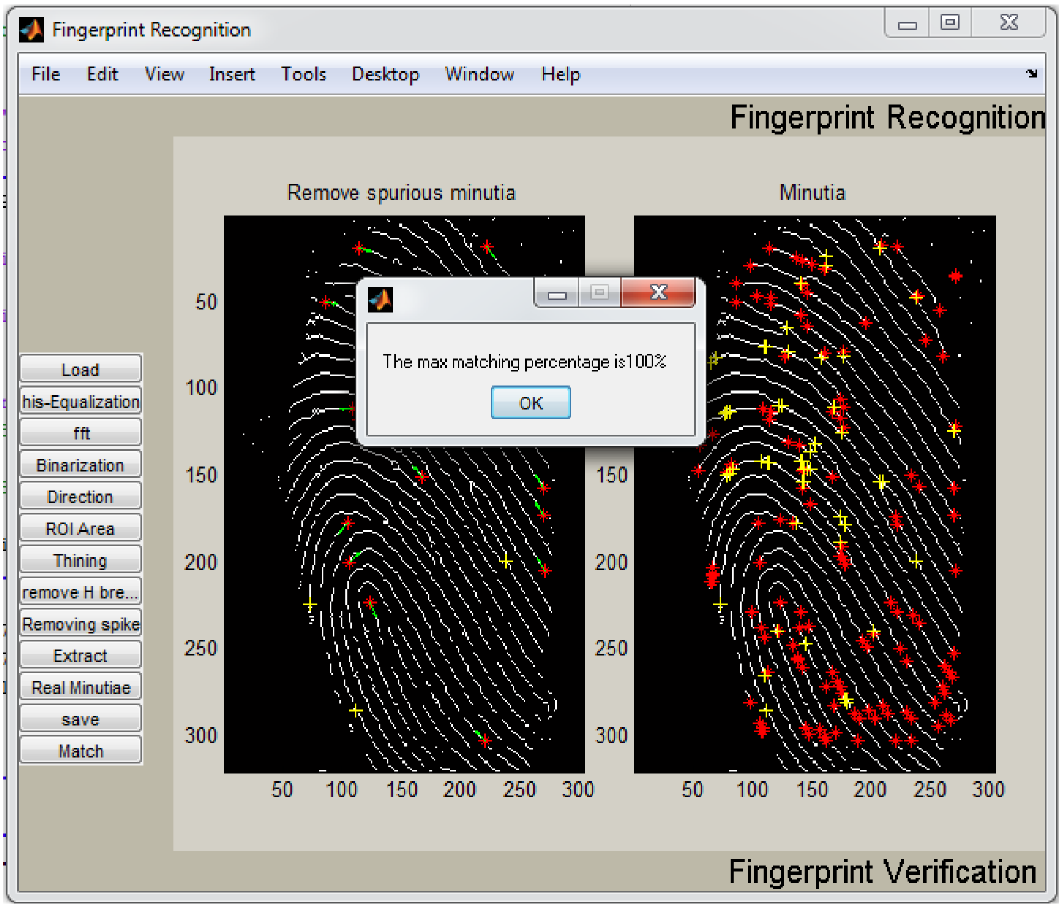
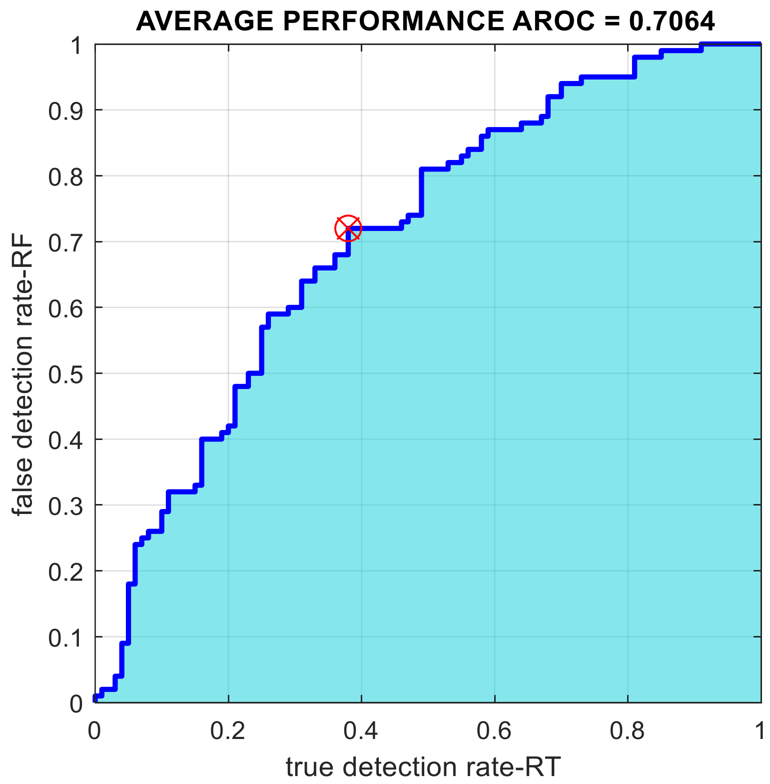
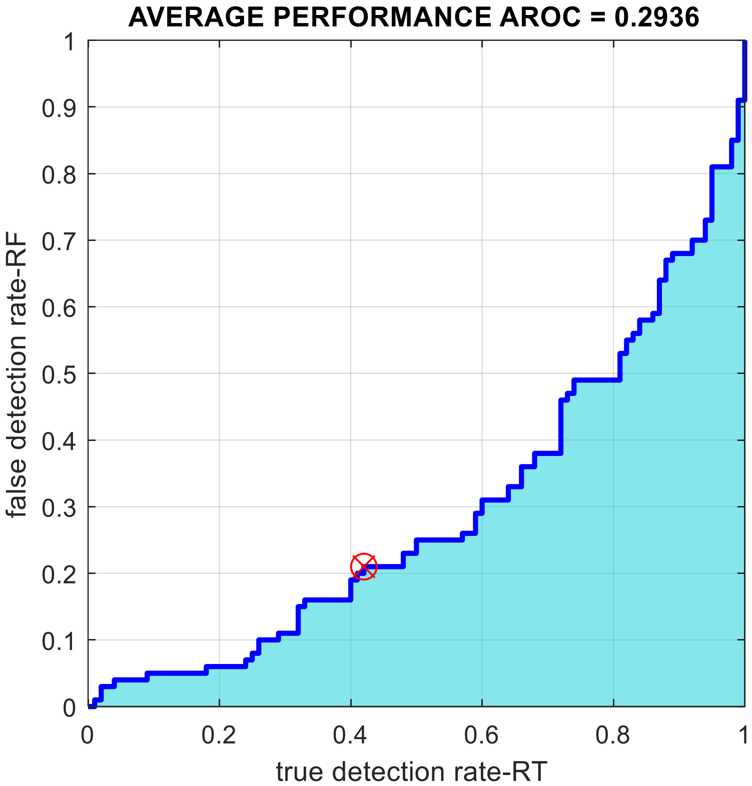



**Figure 9.** Fingerprint verified.






(b)

**Figure 10.** Detection rate graph.

## Experimental Analysis

Experimental analysis of matching minutiae fingerprints involves the systematic examination and comparison of ridge characteristics to establish a conclusive link between two or more prints as shown in Figures 10 and 11 and Table 3.

**Table 3.** Comparison of existing methods and proposed methods

| Parameters Selection | Existing Approach | Proposed Approach |
|---|---|---|
| Distance: | 0.4720 | 0.8947 |
| Threshold: | 0.1928 | 0.5170 |
| Sensitivity: | 0.7200 | 0.2100 |
| Specificity: | 0.6200 | 0.5800 |
| AROC: | 0.7064 | 0.2936 |
| Accuracy: | 0.6700 | 0.3950 |
| PPV: | 0.6545 | 0.3333 |
| NPV: | 0.6889 | 0.4234 |
| FNR: | 0.2800 | 0.7900 |
| FPR: | 0.3800 | 0.4200 |
| FDR: | 0.3455 | 0.6667 |
| FOR: | 0.3111 | 0.5766 |
| F1 score: | 0.6857 | 0.2577 |
| MCC: | 0.3417 | -0.2260 |
| BM: | 0.3400 | -0.2100 |
| MK: | 0.3434 | -0.2433 |

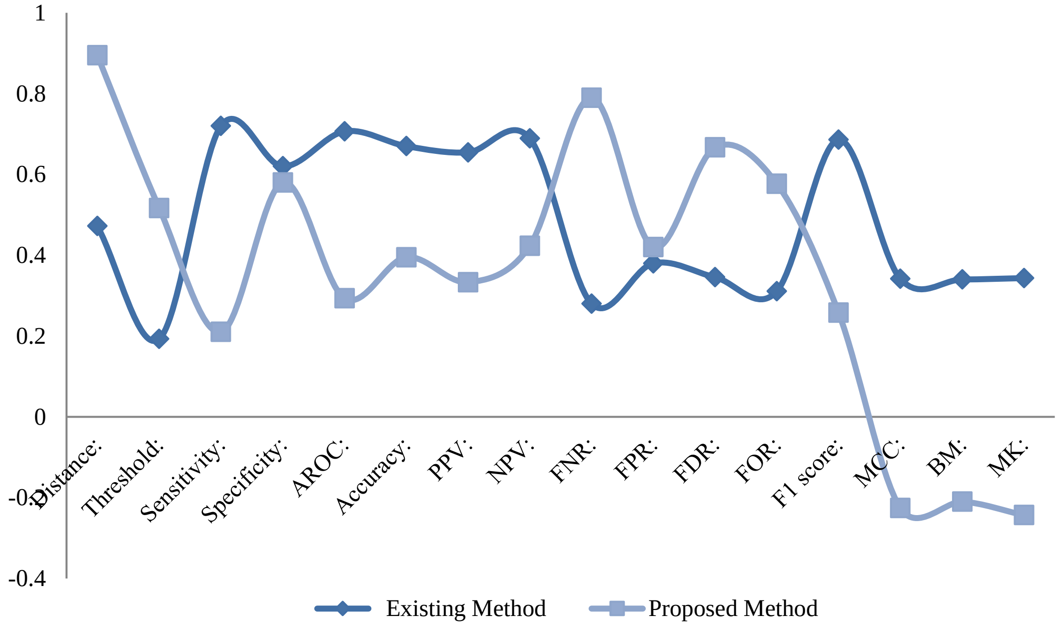



**Figure 11.** Comparison between the existing method and the proposed method.

## CONCLUSION

Existing methods are for quickly improving fingerprinting and displaying quick details. Image projection is to enhance finger image and remove noise in finger image, which aids in eliminating errors at the minute point. Content algorithms are faster because they use smaller samples for accuracy than other fingerprint-based algorithms. If the fingerprint is not comprehensive, for example, is not good and the audio can create a lot of false details where there is no real content. A new minutiae extraction and matching framework, known as the Q-Learning minutiae point detection algorithm, has been introduced in this paper for the purposes of fingerprint identification and verification. Q-Learning minutiae point detection is presented in this study as a solution to the problems of slow convergence speed and low search accuracy in the later stages. Therefore, the best way to extract Q-Learning details is to use a contemporary finger recognition system framework, which offers better performance compared to too many cutting-edge techniques in terms of AROC, accuracy, and other metrics.

## REFERENCES

1. Maltoni D, Maio D, Jain AK, Prabhakar S. Handbook of Fingerprint Recognition. New York, NY: Springer; 2009.
2. Cappelli R, Ferrara M. A fingerprint retrieval system based on level-1 and level-2 features. Expert Syst Appl. 2012; 39 (12): 10465–10478.
3. Pankanti S, Prabhakar S, Jain AK. On the individuality of fingerprints. IEEE Trans Pattern Anal Mach Intell. 2002; 24 (8): 1010–1025.
4. Zhao Q, Jain AK. On the utility of extended fingerprint features: a study on pores. In: 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition – Workshops, June 13, 2010. pp. 9–16.
5. Nogueira RF, de Alencar Lotufo R, Machado RC. Evaluating software-based fingerprint liveness detection using convolutional networks and local binary patterns. In: 2014 IEEE Workshop on Biometric Measurements and Systems for Security and Medical Applications (BIOMS) Proceedings, October 17, 2014. pp. 22–29.
6. Wu CP, Li WC. Three-dimensional static analysis of nanoplates and graphene sheets by using Eringen's nonlocal elasticity theory and the perturbation method. Computers Mater Continua. 2016; 52 (2): 73–103.
7. Jain AK, Chen Y, Demirkus M. Pores and ridges: high-resolution fingerprint matching using level 3 features. IEEE Trans Pattern Anal Mach Intell. 2006; 29 (1): 15–27.

8. Lee W, Cho S, Choi H, Kim J. Partial fingerprint matching using minutiae and ridge shape features for small fingerprint scanners. Expert Syst Appl. 2017; 87: 183–198.
9. Zhang F, Xin S, Feng J. Combining global and minutia deep features for partial high-resolution fingerprint matching. Pattern Recogn Lett. 2019; 119: 139–147.
10. Khodadoust J, Khodadoust AM. Fingerprint indexing based on minutiae pairs and convex core point. Pattern Recogn. 2017; 67: 110–126.
11. Galar M, Derrac J, Peralta D, Triguero I, Paternain D, Lopez-Molina C, García S, Benítez JM, Pagola M, Barrenechea E, Bustince H. A survey of fingerprint classification part I: taxonomies on feature extraction methods and learning models. Knowledge-Based Syst. 2015; 81: 76–97.
12. Zhang P, Li C, Hu J. A pitfall in fingerprint features extraction. In: 2010 IEEE 11th International Conference on Control Automation Robotics & Vision, December 7, 2010. pp. 13–18.
13. Zhang D, Liu F, Zhao Q, Lu G, Luo N. Selecting a reference high resolution for fingerprint recognition using minutiae and pores. IEEE Trans Instrum Meas. 2010; 60 (3): 863–871.
14. Ismaeil AM. Fingerprint Image Quality Analysis and Enhancement Using Fuzzy Logic Technique. Doctoral Dissertation. Khartoum, Sudan: Sudan University of Science and Technology; 2017.
15. Zhang F, Xin S, Feng J. Combining global and minutia deep features for partial high-resolution fingerprint matching. Pattern Recogn Lett. 2019; 119: 139–147.
16. Choi HY, Jang HU, Kim D, Son J, Mun SM, Choi S, Lee HK. Detecting composite image manipulation based on deep neural networks. In: 2017 IEEE International Conference on Systems, Signals and Image Processing (IWSSIP), May 22, 2017. pp. 1–5.
17. Sripavithra S, Akalya S, Rajarajeswari S, Kannan J, Sumathi N. Fingerprint detection using minutiae extraction. Int J Res Appl Sci Eng Technol. 2017; 5 (III): 672–675.
18. Bakheet S, Al-Hamadi A. Hand gesture recognition using optimized local Gabor features. J Comput Theor Nanosci. 2017; 14 (3): 1380–1389.
19. Dabouei A, Kazemi H, Iranmanesh SM, Dawson J, Nasrabadi NM. Fingerprint distortion rectification using deep convolutional neural networks. In: 2018 IEEE International Conference on Biometrics (ICB), February 20, 2018. pp. 1–8.