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A Comparison between Backpropagation Neural Network and Seven Moments for More Accurate Fingerprint Video Frames Recognition

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Abstract

In this modern age of electronic interactions, more secure methods are required to protect vital information. Passwords are indeed a prominent and secure method, but they are subject to being forgotten, especially if they are long and complex. A more efficient way is the use of human fingerprints, which are unique to each person. No two people would have the same fingerprint even if they were a twin, which makes it a very secure method that cannot be duplicated or forgotten. This research aims to compare seven moments and backpropagation for more accurate fingerprint recognition within video frames. The first method is the "seven moments," and the second method is the Backpropagation Neural Network (BPNN), both applied to the interest points that are extracted from each frame. For extracting the interest points from each one of the frames, Smallest Univalue Segment Assimilating Nucleus (SUSAN), a corner detector, was employed. Multiple examples of video frames were used in comparison, and the findings demonstrated that the BPNN approach was more accurate even when the fingerprint had a significant amount of corrupted data or unclear image pixels.

Keywords: BackPropagation**,** Fingerprint**,** Recognition**,** Seven Moments, SUSAN Detector.

Introduction

Biometrics refers to an automated procedure of realizing an individual based on their behavioral or physical characteristics, such as fingerprints, face, iris, voice, signature, or gait. These characteristics are oftentimes referred to as modalities of biometrics or cue of biometrics. Over the past years, a number of diverse modalities of biometrics were explored to be utilized in various applications ranging from the systems of personal device access to the systems of border control [1]. The progress in the elicitation of patterns has accelerated lately due to numerous emerging implementations that are computationally more exacting, as evident in optical. The most substantial feature of biometrics is that a classification of the biometrics is permanently implemented via a person. Therefore, there is a minimal chance of forgetting or losing it, and it is impossible to steal or lose the identity of biometrics. In particular, the fingerprint is one of the most substantial techniques of biometrics employed to identify a person [2]. The following are some benefits of utilizing a backpropagation algorithm: the only parameter that may be adjusted is the number of inputs. It doesn't need any prior network expertise and is incredibly flexible and effective. It is a routine procedure that typically functions properly.

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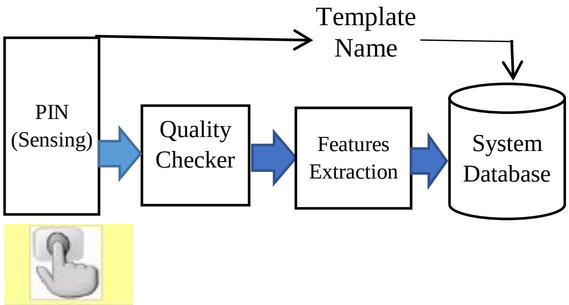
Fingerprint Recognition

The recognition of fingerprints is the most utilized method to identify people compared to different techniques of biometrics due to several reasons, like high distinctiveness, ease of capture, and persistence over time. Moreover, the sensors of fingerprints are cheaper and smaller compared with other sensors of biometrics [3]. A system of biometrics is employed to identify a person by employing his/her features, like behavioral and biological features. Specifically, biological features depend on the physical portion of the human body, like fingerprint, face, iris, speech, and retina, which are used in applications like the system of law enforcement, access control, IT security, and the border management system [4]. On the other hand, behavioral features depend on an action taken by a human, like a keystroke scan, voice, and signature scan. Fig. 1 illustrates the major steps of fingerprint recognition [5]. Therefore, the fingerprint is a collection of numerous ridges and numerous valleys on the surface of the fingertip, where the ridge defines "black" lines and the valleys define "white" lines, as shown in Fig. 2 for some samples of fingerprints [6].

Enrollment



Identification

Related work

There are different researches in the field of fingerprint recognition, enhancement and matching. The next works introduce the most significant fingerprint recognition

1. The suggested technique in [7] established an embedded image processing algorithm depending on a Siamese NN in the recognition approach which enables the suggested technique to recognize images from all sources without initially building a database for image storage. The suggested approach was used in this study to recognize fingerprints, and its effectiveness was assessed. The findings revealed that the suggested algorithm's F1 score could reach 0.87 and that its accuracy could reach 92%. Its considerable advantage in FAR, FRR, and CR together revealed the extraordinary correct recognition rate of the suggested approach when compared to the traditional fingerprint matching techniques.

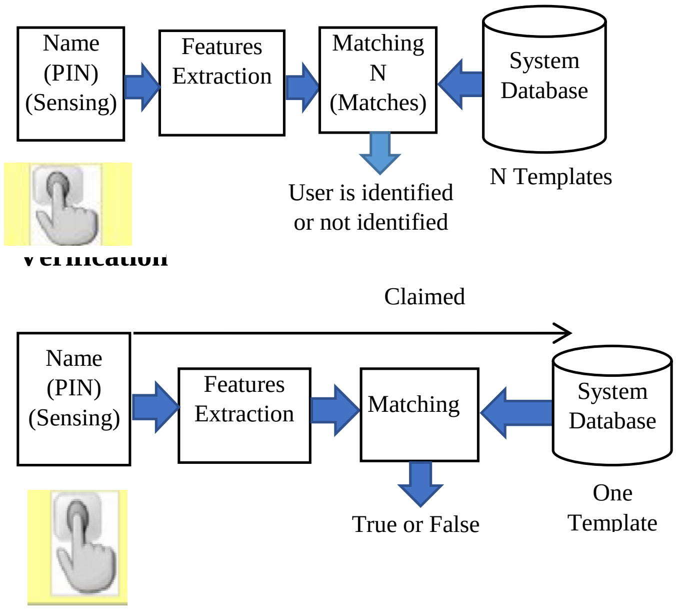


Figure 1. Major stages of verification, identification and enrollment [5].

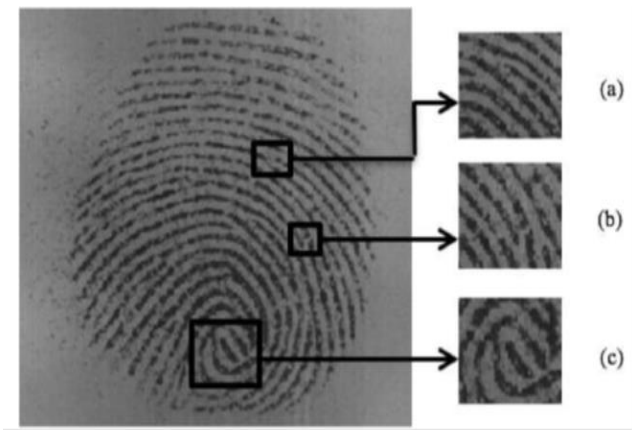


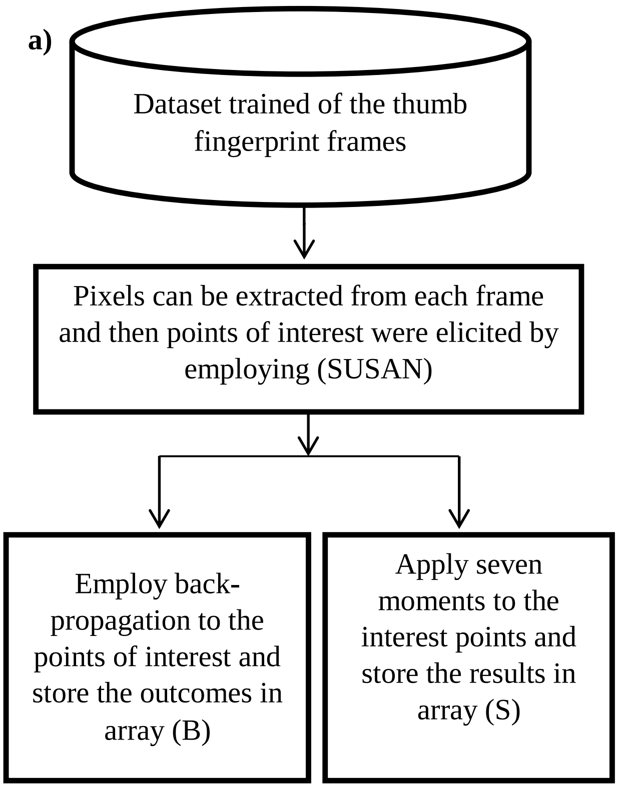
Figure 2. Fingerprint-image with highlighted-minutiae (a) "ridge bifurcation" (b) "ridge ending" (C) "singular region" [6].

2. A fingerprint recognition workflow for modern smartphones was suggested by the study in [8]. The procedure can automatically detect a subject's four inner hand fingers and divide them into individual fingerprint images. The study collected a database of 1,360 fingerprints from 29 people using this method. The study utilized two distinct setups: a tripod configuration and a box setup with limited environmental influences. The suggested approach, which is made available to the public, serves as the foundation for a touchless automatic fingerprint recognition system for mobile devices. Researchers are urged to include their algorithms in the system so as to develop a touchless fingerprint recognition system that is more reliable, accurate, and safe.
3. An investigation towards a learning-based approach to fingerprint recognition may be found in work[9]. Deep learning (DL) technologies were effectively used to improve the AFIS's performance with regard to speed of matching and search time amongst fingerprint databases. For classifying fingerprints as well as predicting their types, a CNN model was constructed. The suggested classification scheme is a new method for grouping fingerprints according to figure type. The suggested CNN model was trained and tested using two open datasets. With high validation accuracy across both datasets, the suggested model was able for predicting the types of fingerprints with an average accuracy of almost 94%

Comparison Methods

A suggested method for fingerprint recognition consists of four main steps. The first stage requires uploading a video and then extracting the trained frames of the thumb fingerprint on the execution screen, extracting the pixels from each frame, where pixels can be extracted from each frame and then points of interest are elicited by employing the corner detector of SUSAN. The back-propagation neural network is employed to the interest points in the second stage, storing the results in array (b), applying seven moments to the points of interest, and then stockpiling the outcomes in an array (s). In the third stage, a test of the thumb fingerprint is entered, where pixels can be extracted from the test frame, and points of interest are elicited by employing the corner detector of SUSAN and then applying the back-propagation and the seven moments to the tested image. For the fourth step, it can compare the back-propagation values of the tested frame with an array b [], and it can compare the seven moments values of the tested image with an array s [] to recognize the extent of conformity of the tested image with the training images for the two methods. The flowchart of the suggested approach can be seen in Fig. 3.

a)



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b)

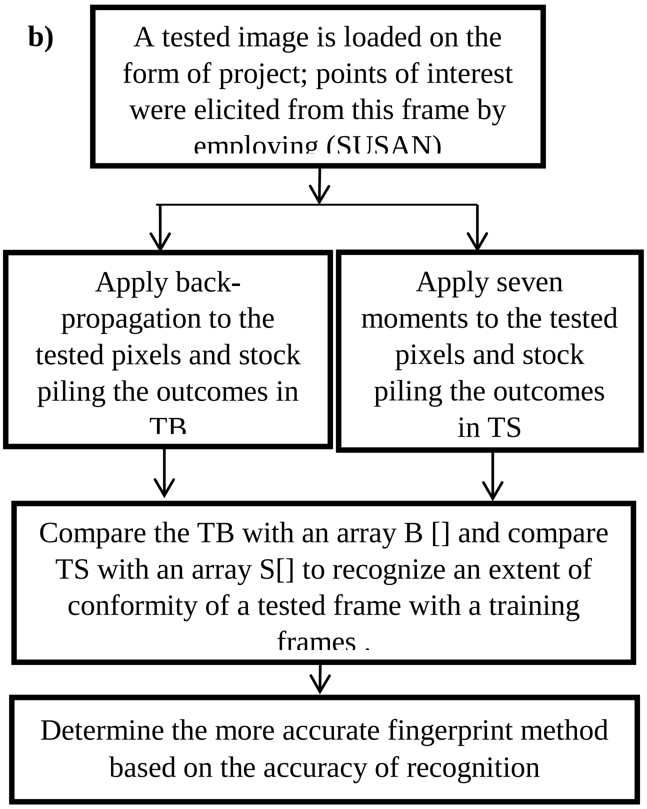

Figure 3. The flowchart of the proposed methodology. a) For training phase and b) for testing phase.

An Algorithm of (SUSAN) Detector

The SUSAN method was shown using a circular mask with a nucleus pixel in the center. In the case when a pixel mask's brightness is put to comparison with the brightness of a nucleus, the region of the mask will be built using the nucleus' brightness as a benchmark. The region of the mask in this case is denoted by (USAN), and it could be derived from (Univalue Segment Assimilating Nucleus) [10]. Each mask's nucleus and pixel contain a function that is used to evoke a corner. Eq. 1 could be used for comparison**.**

$$comp(pix, pix_0) = \begin{cases} 1 & |img(pix) - img(pix_0)| < thr; \\ 0 & otherwise \end{cases} \quad \ldots..1$$

where (pix_0) refers to the coordinates of pixel-nucleus, *pix* refers to the *coordinates' pixel of other points on the mask*, (*comp*(pix_0, *pix*)) refers to the comparison task's outcomes, (*Img*(*pix*)) offers the gray-rate within a pixel point, and *(thr)* offers the gray difference's threshold, which can be utilized for detecting the minimum contrast and the characteristic domain ability dimension determined by the SUSAN approach [11].

The comparison is between mask's pixels. Eq. 2 can be employed to compute the (total (n)).

$$n(pix_0) = \sum_{pix} comp(pix, pix_0) \quad \ldots..2$$

Where (total (n)) displays the pixels' number within the (USAN) zone. "n " will be compared then within a particular threshold "g", which is set to be exactly half of n_{max} to the actuality of that zone of (USAN), which should be lower compared with the half of the mask area if the sites of the nucleus in a corner. Eq. 3 can be utilized to construct a response of initial corner**.**

$$RC(pix_0) = \begin{cases} 1\ g - n(pix_0) & if\ n(pix_0) < g; \\ 0 & otherwise \end{cases} \quad \ldots..3$$

Where Rc (pix_0) refers to the response of initial corner [11]. The SUSAN algorithm's conceptual diagram is displayed in Fig. 4. The image surface is represented by the dark area. The USAN area decreases to its lowest value in the case when the nucleus is at a corner, as shown in Fig. 4(a), and it increases when the nucleus gets closer to the surface, as shown in Fig. 4(b) and (c), respectively.

The USAN area achieves its maximum when the nucleus totally resides in the flat zone, as shown in Fig 4(d).

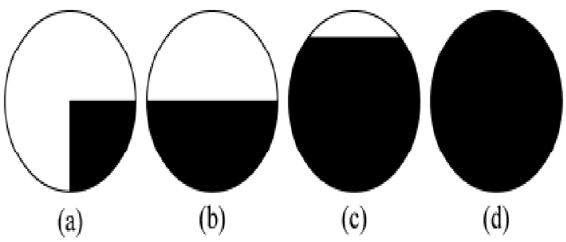

Figure 4. Representative of USAN, (a) USAN area reaches the minimum. (b) USAN area expands; (c) USAN area expands even further. (d) USAN area reaches the maximum [11].

Backpropagation Neural Network

It can be defined as a network consisting of various layers that are interconnected. Backpropagation refers to backward errors' propagation in combination with a method of optimization, such as a descent of steepest. It computes the local minima with regard to the weights associated to the

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network. The weights can be accordingly updated for reducing local minima. Since this network depends on a familiar target outcome for each input fed to a network, it is considered a method of supervised learning [12]. The algorithm consists of two major steps including:

1. The Step of Propagation:-
- Propagation of the forward path: - The input is specified to a network in order to produce the outcomes of propagation.
- Propagation of the backward path: - The feedback network is advanced by providing the outcome as an input for evaluating the difference between the target and the actual outcomes [13].

2. The Step of updating the weights:-
- A weight's gradient is a result of various calculations among the activation of outcomes and input.
- Subtract a percentage of the gradient from the weight [13]. Fig. 5 exhibits a principal diagram of the backpropagation algorithm.

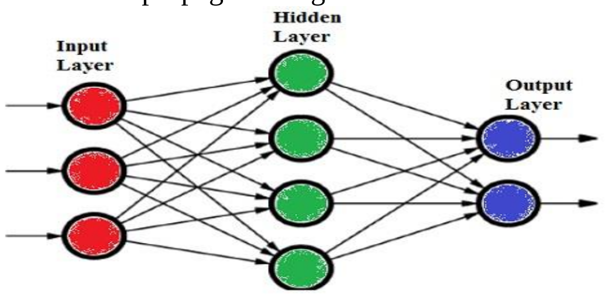

Figure 5. The main layers of Backpropagation algorithm [14].

Moment Invariants

The invariants of the moment had been vastly employed to recognize a pattern within an image in a variety of usages due to its features' invariant on image rotation, scaling, and translation. The moments are strictly invariant for the continuous function. In practical employment, images are discrete. The invariants of the moment may be modified during a geometric transformation of an image [15]. Suppose the (F (x, y)) defines a 2-Dim image within a spatial model. The geometric moment regarding arrangement *"p + q"* can be constructed through Eq. 5.

$$m_{p,q} = \sum_x \sum_y x^p y^q F(x,y) \quad \text{.....5}$$

For" *p, q* = 0, 1, 2 ... " .A central of moments can be constructed using Eq. 6.

$$x_c = m_{1,0} / m_{0,0}$$
$$y_c = m_{0,1} / m_{0,0} \quad \text{.....6}$$

Where (xc and yc) in Eq. 6 refer to the region's center within an object. Hence, the *Central moments are* of order up to 3. The normalized moments' central indicate $\eta_{p,q}$, as explained in Eq. 7.

$$\eta_{p,q} = \mu_{p,q} / \mu^{\gamma}{}_{0,0} \quad \text{.....7}$$

Where

$$\gamma = p + q/2 \quad \text{.....8}$$

For "Eq. 8", "p + q = 2, 3,…,p*q". A group of (7) *transformations moments invariant* constructed by 2nd order and 3rd order moments using Eq. 9 [16]. This set of central normalized moments is fixed to changes in an image's translation, scale, and rotation 16.

$$\left.\begin{array}{l}
\phi 1 = \eta_{2,0} + \eta_{0,2} \\
\phi 2 = (\eta_{2,0} + \eta_{0,2})^2 + 4\eta_{1,1} \\
\phi 3 = (\eta_{3,0} - 3\eta_{1,2})^2 + (3\eta_{2,1} - \eta_{0,3})^2 \\
\phi 4 = (\eta_{3,0} + 3\eta_{1,2})^2 + (3\eta_{2,1} + \eta_{0,3})^2 \\
\phi 5 = (\eta_{3,0} - 3\eta_{1,2})(\eta_{3,0} + 3\eta_{1,2})[(\eta_{3,0} + 3\eta_{1,2})^2 \\
- 3(\eta_{2,1} + \eta_{0,3})^2] + (3\eta_{2,1} - \eta_{0,3})(\eta_{2,1} + \eta_{0,3}) \\
[3(\eta_{3,0} + \eta_{1,2})^2 - (\eta_{2,1} + \eta_{0,3})^2] \\
\phi 6 = (\eta_{2,0} + \eta_{0,2})[(\eta_{3,0} + \eta_{1,2})^2 - (\eta_{2,1} - \eta_{0,3})^2] \\
+ 4\eta_{1,1}(\eta_{3,0} + \eta_{1,2})(\eta_{2,1} - \eta_{0,3}) \\
\phi 7 = (3\eta_{2,1} - \eta_{0,3})(\eta_{3,0} + \eta_{1,2})[(\eta_{3,0} + \eta_{1,2})^2 \\
- 3(\eta_{2,1} + \eta_{0,3})^2] + (3\eta_{1,2} - \eta_{3,0})(\eta_{2,1} + \eta_{0,3}) \\
[3(\eta_{3,0} + \eta_{1,2})^2 - (\eta_{2,1} - \eta_{0,3})^2]
\end{array}\right\} \quad \text{..9}$$

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Results and Discussion

The outcomes of empirical results regarding the suggested method are presented and shown in this section. (C#) the language was utilized to perform the suggested methodology. Three kinds of data sets were employed for the estimation of the method. The numbers of images employed are 30 for each type. Images within the data set were "JPEG" colored of bulk 100 × 100 pixels.

The proposed methodology involves the following two main stages: -

1) The video stream is loaded in the first stage and all frames are elicited as shown in Fig. 6 for sample 1, Fig. 7 for sample 2, and Fig. 8 for sample 3.

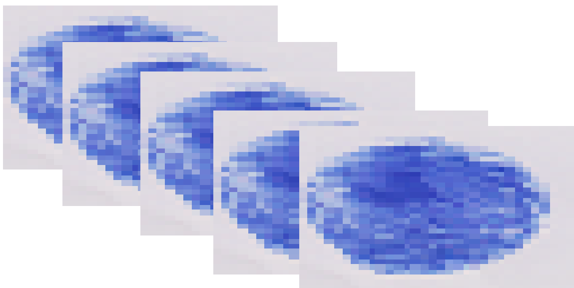

Figure 6. Frames from video sample 1

Figure 7. Frames from video sample 2

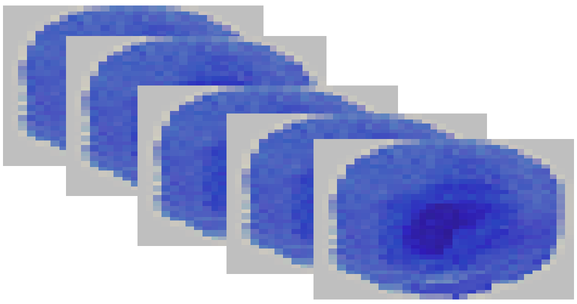

Figure 8. Frames from video sample 3

2) In the second step, it can be employed the SUSAN detector for detecting the interest points (corners) from each frame. Fig. 9 illustrates the results of the SUSAN corner detector on frames of video sample 1.

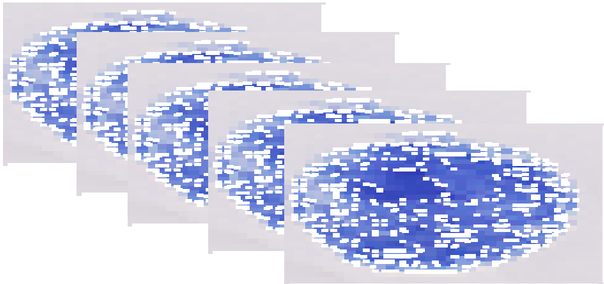

Figure 9. SUSAN corner detector on a frame of video sample 1

3) The back-propagation neural network method was applied to all interest points (corners) of each frame, then it can be applied the seven moments method to interest points (corners) of each frame, and then it can be computed the recognition speed for both methods, as illustrated in Table 1.

Speed values depend on the time for the thumbprint fingerprint recognition. Because the time taken to calculate the backpropagation neural network equations is very long, therefore, the speed of fingerprint recognition is very small. Table1 illustrates the comparison of the algorithms (backpropagation and seven moments). Due to the high degree of time for BPNN, the speed values of the recognition rate are low

Table 1. Thumbprint recognition speed using the BPNN and the seven moment's methods

Sample	Speed using the back propagation method	Speed using the seven moments method
Frame1_Video Sample1	0.998808165	2.1379774
Frame13_Video Sample1	0.998808169	2.22389774
Frame5_Video Sample2	0.998899756	3.76797879
Frame21_Video Sample2	0.998899740	3.37797879
Frame7_Video Sample3	0.998938076	4.63181973
Frame33_Video Sample3	0.998938093	4.1318197

The accuracy of the suggested technique, which is determined by the measurements of sensitivity and

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specificity could be used for calculating the performance of the approach, as shown in Eq. 10 [17].

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} x100 \quad \ldots..10$$

In which TP represents true positive predication, TN represents true negative predication, FP represents false positive predication, and FN represents false negative predication [17].

The degree of complexity of any algorithm depends on the time it takes to execute that algorithm. Therefore, the backpropagation method is considered the most complex because it takes time in the calculations, and since the performance of any algorithm is calculated for the correct recognition rate, the backpropagation is the highest performance compared to the seven moments.

Table 2 illustrates the comparison of fingerprint recognition between the backpropagation neural network (BPNN) method and the seven-moment's method based on some characteristics.

Table 2. Comparison between the backpropagation neural network and the seven moments methods.

Characteristics	BPNN	Seven Moments
Performance	**92.32%**	**87.5%**
Accuracy	**96 %**	**75%**
Complexity	**89.33%**	**64.7%**
Speed	**70%**	**94%**
Authentication	**91%**	**77%**

From Table 2, it could be seen that the characteristics of the performance, security, accuracy recognition, and authentication for the BPNN are higher than those of the seven moments method because the number of incorrect attempts to recognize the fingerprint was small in the BPNN method, and the complexity and speed are lower than those of the seven moments method because the time taken to calculate the BPNN equations is very large. The experimental outcomes show that the performance regarding the BPNN approach is 92.32% compared to the seven-moment method, which is 87.5%, and the accuracy of the BPNN method is higher than that of the seven moment's method, where the performance value was 96% for BPNN, while in the seven-moment it was 75%. The BPNN method is characterized by the highest level of security, as the value was 89.33, while in the seven moments, it was 64.7. The main difference between the proposed system and others is the dependence of the proposed system on a few interest features that are extracted from each frame using the SUSAN method, and this increases the speed of implementation and reduces the storage space, while the previous methods relied on extracting all the features from the images and not only the important features, which leads to any slowdown in the process Implementation in addition to the need for large storage spaces. This solution outperforms others by increasing the speed of fingerprint recognition, the lack of storage space for features, and accuracy in the recognition process, noting that all fingerprint images are real.

Conclusion and Future Works

The recognition of fingerprints is the most utilized method to identify people compared to different techniques of biometrics due to several reasons, like high distinctiveness, ease of capture, and persistence over time. In addition, the sensors of fingerprint are cheaper and smaller compared with other sensors of biometrics. The proposed methodology for fingerprint recognition has four stages. In the first stage, it can upload the trained frames of the thumb fingerprint on the execution screen and then extract the interest points from each frame using the SUSAN corner detector, which took minimal time to elicit the points of interest, but generated more features. The back-propagation neural network was applied in the first stage to each frame; and it can apply the seven moments to each frame in the second step. For the third stage, a test of the thumb fingerprint was entered and then it can be applied the back-propagation and the seven moments to the tested image. In the fourth stage, it can compute the speed for tested image recognition for both back-propagation and seven-moment's methods. Biometrics refers to an automated procedure of realizing an individual based on their behavioral or physical characteristics, such as fingerprints, face, iris, voice, signature, or gait. These characteristics are oftentimes referred to as modalities of biometrics or cue of biometrics.

The progress in the elicitation of patterns has accelerated lately due to numerous emerging implementations that are computationally more exacting, as evident in optical. The most substantial feature of biometrics is that a classification of the biometrics is permanently implemented via a person. Therefore, there is a minimal chance of forgetting or losing it, and it is impossible to steal or lose the identity of biometrics. In particular, the fingerprint is one of the most substantial techniques of biometrics employed to identify a person. The following are some benefits of utilizing a backpropagation algorithm: The only parameter that may be adjusted is the number of inputs. It doesn't need any prior network expertise and is incredibly flexible and effective. It is a routine procedure that typically functions properly. It can be concluded that in Table 2 the performance of the BPNN method is 92.32% compared to the seven-moment's method, which is 87.5%, and the accuracy of the BPNN method is higher than that of the seven moment's method, where the performance value was 96% for BPNN, while in the seven moments it was 75%. The BPNN method is characterized by the highest level of security, as the value was 89.33, while in the seven moments, it was 64.7. The speed of BPNN in fingerprint recognition is lower than 70% than the seven-moment's method, which is 94%. Moreover, the authentication of the BPNN method is higher than that of the seven-moment method. These results specify that the BPNN approach is more powerful in terms of accuracy of recognition and security. For future work, other complex artificial intelligence methods can be used.

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Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at University of Technology.
- Ethics statement:
  No animal studies are present in the manuscript.
  No human studies are present in the manuscript.
  No potentially identified images or data are present in the manuscript.

Authors' Contribution Statement

E.T. K. wrote the research in the primitive image (the theoretical part). E.F. N. collected the samples of videos, extracted all frames from each video and then analyzed all colors for encryption (practical part of manuscript). A.T. M. and E.S.M. did the interpretation, drafting the MS, revision, and proofreading.

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مقارنة بين الشبكة العصبية Backpropagation والعزوم السبع للتعرف على بصمات الأصابع في أطارات الفيديو بدقة أكبر

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الخلاصة

في العصر الحديث للتداخلات الإلكترونية ، ظهرت الحاجة إلى طرق أكثر أمانًا لحماية المعلومات الحيوية. كلمات السر هي بالفعل وسيلة بارزة وآمنة ، لكنها عرضة للنسيان ، خاصةً إذا كانت طويلة ومعقدة. الطريقة الأكثر فعالية هي استخدام بصمات الأصابع البشرية. بصمات الأصابع تكون وحيده من نوعها لكل شخص. لا يوجد شخصان لهما نفس البصمة حتى لو كانا توأم. هذا يجعلها طريقة آمنة للغاية والتي لا يمكن تكرارها أو نسيانها. الهدف من هذا البحث هو المقارنة بين الشبكه العصبيه (BPNN) و العزوم السبعه للتعرف على بصمات الأصابع بشكل أكثر دقة داخل إطارات الفيديو. الطريقة الأولى هي تطبيق "العزوم السبعه" والطريقة الثانية هي تطبيق الشبكه العصبيه) على نقاط الاهتمام المستخرجة من كل إطار. تم استخدام كاشف الزاوية SUSAN لاستخراج نقاط الاهتمام من كل إطار. تم تطبيق المقارنة على عدة عينات من إطارات الفيديو وأظهرت النتائج أن طريقة BPNN أثبتت أنها أكثر دقة حتى لو كانت بصمة الإبهام تحتوي على الكثير من البيانات المشوهة أو وحدات البكسل غير الواضحة.

الكلمات المفتاحية: التغذية الخلفية, بصمة الأصبع, التعرف, العزوم السبعة, كاشف سوزان .