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Humans Verification by Adopting Deep Recurrent Fingerphotos Network

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Abstract

Fingerphoto can be considered as one of recent and interesting biometrics. It basically means a fingerprint image that is acquired by a smartphone in contactless manner. This paper proposes a new Deep Recurrent Learning (DRL) approach for verifying humans based on their fingerphoto image. It is called the Deep Recurrent Fingerphotos Network (DRFN). It compromises of input layer, sequence of hidden layers, output layer and essential feedback. The proposed DRFN sequentially accepts fingerphoto images of all personal fingers. It has the capability to change between the weights of each individual fingerphoto and provide verification. A huge number of fingerphoto images have been acquired, arranged, segmented and utilized as a useful dataset in this paper. It is named the Fingerphoto Images of Ten Fingers (FITF) dataset. Average accuracy result of 99.84 % is obtained for personal verification by exploiting fingerphotos.

Keywords: Biometric, Deep Learning, Finger Images, Personal Recognition, Verification.

Introduction

The term 'biometric' is commonly utilized to refer to a technique of recognizing individuals. It has been applied in various domains such as security systems, forensic investigations and personal identification. Numerous characteristics of human's body, such as the iris, sclera, face, palmprint, voice and Finger Texture (FT), have been extensively explored. Biometric recognition plays a crucial role in numerous recognition systems, providing secure access to technological devices such as mobile phones, laptops and Automated Teller Machines (ATMs). Biometric characteristics are commonly classified into two categories: physiological biometrics and behavioral biometrics. Examples of physiological biometrics are fingerprints, iris patterns, palm prints and fingerphotos. They are utilized for high reliability. Examples of behavioral biometrics are signatures, keystroke dynamics and voice. Such biometrics are influenced by emotional states, which potentially impact their reliabilities [1].

Biometric identification methods have revolutionized security measures, leveraging various unique traits [2,3]. There are many useful biometric traits in fingers such as Finger Geometry (FG) [4,5], Finger Veins (FV) [6,7], Finger Outer Knuckle (FOK)[8],

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Finger Inner Knuckle (FIK)[9,10] and Finger Texture (FT) [11,12]. Each of these characteristics can provide a significant level of importance. However, recent studies have emphasized the fingerphoto as a significant biometric[13–16]. It basically refers to a fingerprint that is taken by a smart phone, with no direct touching (contactless).

Fingerprint of fingerphoto has similar concepts of fingerprint characteristic. Fingerprints serve as one of the most well-known biometrics. They have been exploited because for their uniqueness. Every individual possesses a collection of distinct ridges and swirls, which provide the ideal means of personal recognition. Fingerprint has become essential for forensic investigations, assisting law enforcement agencies around the world in resolving crimes. Moreover, their applications have been extended for various fields, including secure access to systems, immigration controls and pass security borders. The enduring and unchanging nature of fingerprints throughout any individual's lifetime emphasize pivotal role in ensuring precision and dependability in the matters of recognition and security. The enduring biological characteristic of fingerprint continues to be essential tool in society, safeguarding individuals and communities [17–20]. Fingerprints possess valuable features including assemble, ridge crossing, bifurcation, core, enclosure, ridge ending and delta shape. These features are illustrated in Fig. 1 [21]. Again, the fingerphoto refers to a fingerprint which is acquired by a smart phone. An example of a fingerphoto image is shown in Fig. 2.

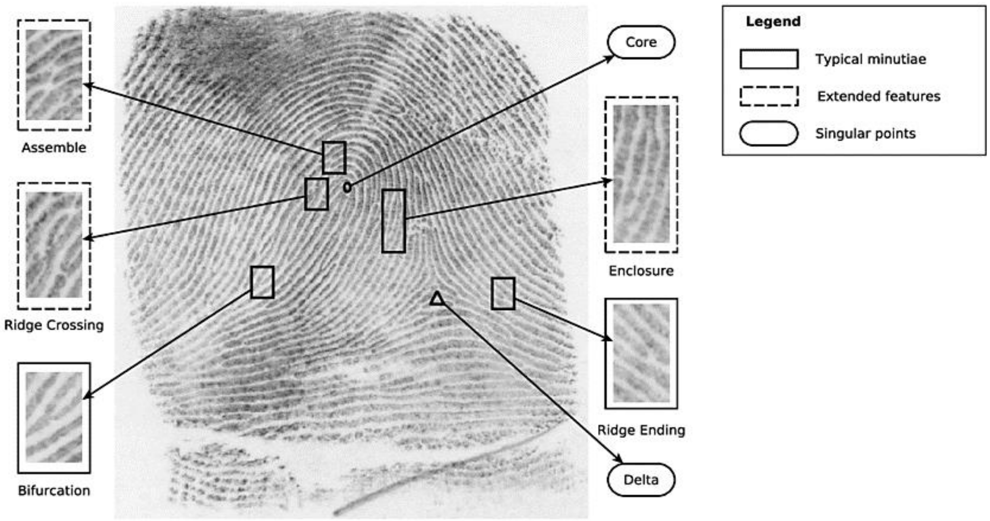

Figure 1. Demonstration of different fingerprint features.

Figure 2. Fingerphoto Image Sample

This study aims to verify humans based on their fingerphotos. There are two main contributions here, they can be highlighted as follows:

- Introducing a new dataset called the Fingerphoto Images of Ten Fingers (FITF). This dataset has a hug number of fingerphoto images, where ten fingers are acquired for each person.
- Presenting a novel Deep Recurrent Learning (DRL) approach termed the Deep Recurrent Fingerphotos Network (DRFN). This approach is proposed for verifying individuals by using fingerphotos.

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Literature Review

Fingerphoto has been emphasized in recent studies. Such studies can be reviewed as follows:

Stein *et al.* proposed an authentication technique that discovers the capacities and execution of fingerprint recognition utilizing smartphone cameras. Improvement of algorithms for capturing and pre-processing images was included. A dataset encompasses images of the two experimental devices was collected from a combined total of only 41 participants [22].

Tiwari *et al.* proposed the implementation of a fingerphoto recognition system for mobile handheld devices that operates without any physical contact and utilized alternative, scale-invariant features. The suggested system for verifying the identity of human users on mobile hand-held devices through fingerphoto analysis avoided dependence on specific scanning devices. The employed dataset consisted of 50 individuals [23].

Birajadar *et al.* integrated a technique of fingerphoto enhancement that relies on monogenic wavelet and employs features of phase congruency. The authors had successfully constructed a dataset for fingerphoto, which had been done under conditions where the environment was unconstrained. A smartphone camera had been utilized in combination with live-scan images. The dataset was composed of 50 subjects, where each subject was associated with 4 images. Consequently, the total number of images in the dataset was reached to 200 [24].

Carney *et al.* established a Multi-Finger Touchless fingerprinting system by utilizing smartphones, which enabled the capture of fingerprints solely through the rear camera and the Light Emitting Diode (LED) flash. This particular system incorporated an automatic image capture mechanism that facilitated the identification and enhancement of each individual finger's corresponding image to simulate a touch-based print. A preliminary test dataset consisting of 1400 touchless fingerprints and 6600 touch-based fingerprints was utilized for evaluation purposes [25].

Deb *et al.* created two Android applications to gather the ridges features of fingerphotos. For the right and left hands, two thumb fingers and two index fingers were only used. After analyzing each finger independently, three fusion procedures were used: fusion between two thumbs or fusion between two indexes; fusion between each hand's thumb and index finger; and fusion of all used fingers (thumb and index of both hands). For every fusion that was used, the summation criteria for combinations of score levels were applied [26].

Al-Nima *et al.* utilized fingerphoto images for the case of individual recognition. Dual Deep Fingerphoto Learning (DDFL) method was suggested. It involved two deep learning networks, each one was called the Deep Fingerphoto Learning (DFL). IIITD smartphone fingerphoto dataset was exploited. It has fingerphoto images of only middle and index fingers for right hands [27].

Al-Nima *et al.* presented additional deep learning techniques study for personal verification based on the Fingerphoto. Couple of Deep Fingerphotos Learning (CDFL) was suggested. The dataset of IIITD smartphone fingerphoto was utilized too. This dataset includes fingerphoto images for just two fingers (middle and index) in right hands [13].

It can be investigated that there is no work consider collecting a dataset of fingerphoto images from the full 10 fingers for a big number of humans and there is no work consider verifying persons by exploiting their full 10 fingerphotos. This study presents the dataset of FITF for and the new verification method of DRFN to address these lacks. To the best obtained knowledge, there is no previous study that consider such contributions.

Methodology

As mentioned, the aim here is to verify humans based on their fingerphotos. The suggested recognition system starts with pre-processing, then, applying the DRFN approach. The pre-processing is employed for all collected fingerphoto images. It mainly consists of segmentation and augmentation. After that, the

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DRFN approach is applied for the case of verification.

Dataset and Pre-processing

First of all, a huge number of fingerphotos has been acquired in a dataset named the FITF. This dataset is collected from 100 individuals by using smartphones. Each person has participated by his/her 10 fingers, where 10 fingerphotos are captured for each finger and to both right and left hands. Captured images have been considered for contactless fingers, which are positioned in a variety angles to ensure comprehensive consideration. The FITF dataset was carefully collected to encompass a diverse range of participants, including a variety of pose variations and lighting conditions, ensuring comprehensive representation. Such dataset establishes the groundwork for our analysis, as well as, it can be utilized for a big range of applications and inquiries.

After collecting the FITF dataset, the initial stage would be acquiring the Region of Interest (ROI) of a fingerphoto. ROI here referes to the objective of isolating the fingerphoto image from a captured raw image. Ensuring consistent orientation among all fingerphoto images is of utmost importance because of the diverse angles which have been considered in capturing. This mandates careful alignment and adjustment for ensuring a uniform visual standpoints. Accomplishing accurate vertical alignment for all fingerphotos provides additionally improvements for the dataset.

To accomplish this, a variety of techniques in the field of image processing, such as thresholding, edge detection, or region growing, are utilized. Furthermore, the utilization of alignment techniques based on moments plays a critical role in refining the segmentation process. These techniques make use of mathematical descriptors known as moments to quantitatively represent the spatial distribution of pixel intensities within the image.

One particular representation of moments that finds application in image processing is the geometric moment, which is denoted as I_{XY} and it is defined as:

$$I_{XY} = \sum_z \sum_n Z^X N^Y M(z,n) \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad 1$$

where X and Y are non-negative integers, Z and N are the pixel coordinates, and $M(z,n)$ represents the pixel intensity at the coordinates (z,n).

Through the utilization of alignment techniques based on moments, the segmentation process is enhanced by aligning the moments of the ROI with a reference model. This adjustment aids in minimizing the impact of noise and interference originating from the surrounding areas. The utilization of moments in the alignment process is particularly advantageous in scenarios where precise registration is of utmost importance, such as in the fields of medical imaging or object recognition applications.

Additional pre-processing operation is utilized; it is referred to as Augmentation. The utilization of Augmentation has the capability to improve the resilience and generalization capability of deep learning models. By implementing transformations such as resizing, rotation and reflection, Augmentation ensures that the images in the dataset conform to the requirements of the deep learning networks. Furthermore, Augmentation is a mitigating key of overfitting, a phenomenon in which the model becomes excessively specialized to the training data and encounters difficulties with unseen samples.

By introducing randomized pre-processing operations, Augmentation introduces variability in the training data for each epoch. As a result, in each training cycle, the model encounters slightly different versions of the data. This diversity in the training set aids the model in acquiring more robust and adaptable features. It is noteworthy that Augmentation also contributes to the efficiency of memory usage. Transformed images are not stored in memory, which offers a distinct advantage when dealing with a large dataset. This operation can significantly enhance the overall effectiveness and reliability of a deep learning model.

Fingerphotos for Verification

In order to explore the potential of fingerphotos for user verification, the verification mode is firstly defined as shown in Fig. 3.

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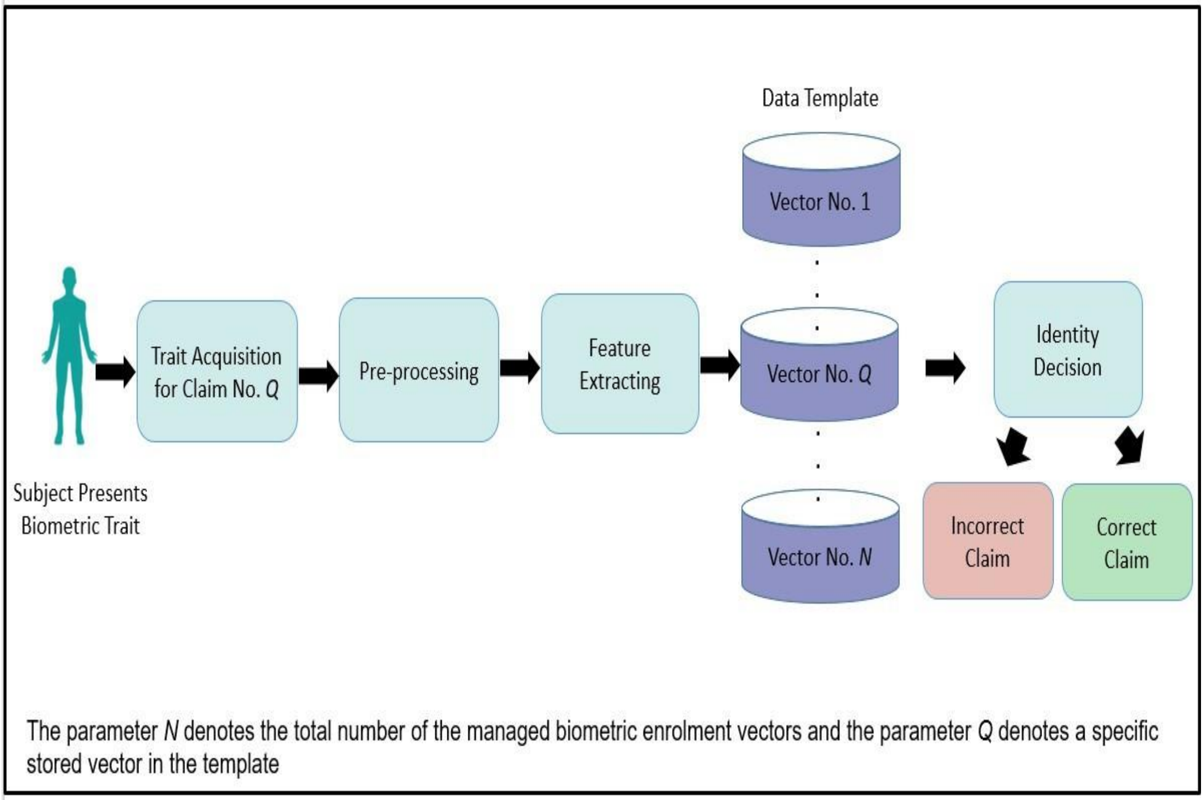

Figure 3. Typical verification mode operations[28]

Basically, in this mode a person claims his/her class number at first. Then, a biometric system considers checking this claim according to information at the certain class and decide if it is correct or not. So, any person who enrolled in a fingerphoto biometric system has to provide his/her class number in order to achieve the verification. The system accepts a fingerphoto image of the little finger of a one hand and check the output class. If the output class appears not correspond to the class number claim, the essential feedback switches to the weights of another finger (the ring finger of the same hand). Subsequently, the system inputs a fingerphoto image of the ring finger and check for the verification again. Such processes are repeated for all fingers of the first hand, then, moves to the fingers of the second hand. The remaining fingers are sequentially input and the verification process is carried out with the same policy.

Proposed DRFN

A DRL approach is proposed, it is named the DRFN. It has the ability to provide feature extraction and verification for fingerphoto images. The proposed DRFN involves multi-layers and essential feedback. It is based on a simple Convolutional Neural Network (CNN)[29,30].The multi-layers are sequentially arranged as: input, convolution, Rectified Linear Unit (ReLU), pooling, Fully Connected (FC), softmax, and classification layers. The essential feedback is so important, it completes the DRL structure and it has the capability to further enhance verification performance. The architecture of the proposed DRFN model can be seen in Fig. 4. Next, the DRFN parts are illustrated.

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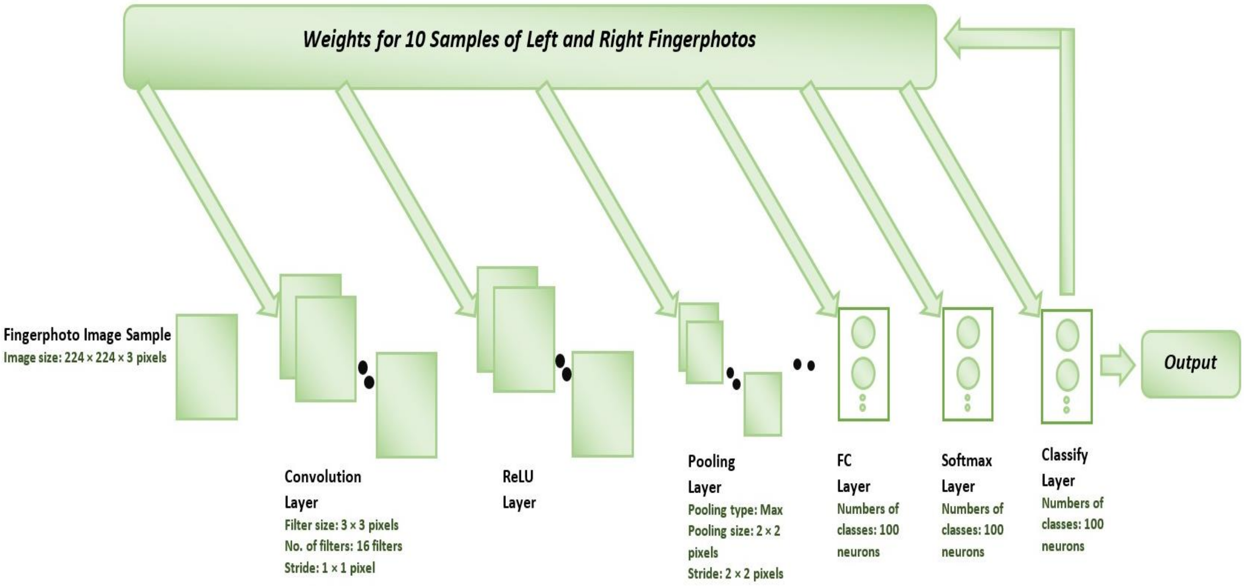

Figure 4. The architecture of the proposed DRFN model.

Input Layer

This particular layer is responsible for handling a fingerphoto input image. Each image sample is of the Red, Green and Blue (RGB) type with the dimensions of (height×width×3) pixels. In simpler terms, the inputs in this layer are represented as colored images of fingerphotos, where each image composes of the three RGB channels **IMF**.

Convolution Layer

The convolution layer generates feature maps which are derived from each channel c_{in} of the input layer. Each feature map serves as a convolved channel with a kernel, where the kernel is a collection of weights. Typically, the kernel possesses a dimension of width w multiplied by height h, illustrated as $w \times h$ pixels. The primary equation for a convolution layer is expressed as follows:

$$V_{z,t,q} = D_q + \sum_{i=1}^{c_{in}} \sum_{j=1}^{k_h} \sum_{k=1}^{k_w} IMF_{z_{S+j},t_{S+k},i} \times W_{j,k,i,q} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 2$$

where $V_{z,t,q}$ represents a value in a convolution feature map, (z, t) represents a spatial coordinate, q refers to the channel index D_q represents the bias associated with the q^{th} feature map in the convolutional layer, $IMF_{z_{S+j},t_{S+k},i}$ denotes a value of the previous i^{th} channel at an adjusted spatial coordinate $(z_{(S+j)}, t_{(S+k)})$ possibly due to the application of a stride S, and $W_{j,k,i,q}$ represents the weight associated with the connection between the i^{th} channel of an input and the q^{th} channel of a convolution feature map at the spatial position (j, k, i, q)[31].

It is worth mentioning that there are biometrics require more than one convolutional layer to be further analyzed. However, it is not appropriate here to add more layer (or layers) in the proposed DRFN model as this increases its complexity, especially it could attain the highest accuracy as will be illustrated in the next section. Therefore, keeping it as simple as possible is better.

ReLU Layer

The primary advantage and purpose of incorporating this particular layer in the model architecture is to facilitate and enable non-linear computations. This accomplished by retaining and preserving only the positive values present in feature maps, while simultaneously discarding and eliminating the negative values. This characteristic of the ReLU activation function plays a pivotal role in enhancing the model's ability to process and analyze the features. The mathematical expression for the calculation of the ReLU activation function can be succinctly encapsulated and represented by the following equation:

$$L_{z,t,q} = f(V_{z,t,q}) = \max(0, V_{z,t,q}) \quad \ldots\ldots\ldots\ldots\ldots \quad 3$$

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where $L_{z,t,q}$ is denotes the outcome within the ReLU layer and max denotes the maximum operation performed on the given input [32].

Pooling Layer

The pooling layer played a vital role in reducing the dimensions of the received channels. It selectively retrieves the maximum or average values from the resultant ReLU outputs. Here, it diminishes the sizes of the acquired features by aggregating the maximum values. The overarching formula regarding the maximum pooling layer can be expressed as follows.

$$k_{a^l,b^l,c} = \max_{0\le a<h_p, 0\le b<w_p} y_{a^l\times h_p+a, b^l\times w_p+b,c} \quad \text{......} \ 4$$

where $k_{a^l,b^l,c}$ is a pooling layer outcome, $0 \le a^l < h_p^l, h_p^l$ is the height of a pooled channel, , $0 \le b^l < w_p^l$, w_p^l is the width of a pooled channel, $0 \le c < c^l = c^{l-1}$, l and *l-1* are respectively refer to the current layer and previous layer, and w_p and h_p respectively represent the width and height of a sub-region that need to be pooled from ReLU outcomes [33].

FC Layer

The purpose of this layer is to establish well matching between the preceding layer and a specific quantity of neurons. It possesses the capability to effectively establish a correspondence between both the pooling layer and the desired number of classes or subjects (outputs). The functioning of the fully connected layer is mathematically defined as follows:

$$FL_r = \sum_{a=1}^{mc_1^{l-1}} \sum_{b=1}^{mc_2^{l-1}} \sum_{c=1}^{mc_3^{l-1}} W_{a,b,c,r}^l \ (\mathbf{K})_{a,b} \quad \forall 1 \le r \le mc^l \quad \text{..........................} \ 5$$

where FL_r denotes an output of the FC layer, mc_1^{l-1} signifies the height of a channel within the pooling layer, mc_2^{l-1} represents the width of a channel within the pooling layer, mc_3^{l-1} denotes the number of channels created within the pooling layer, $W_{a,b,c,r}^l$ means the linking weights that connect the pooling layer with the FC layer, **K** represents the outputs of the pooling layer and mc^l signifies the number of neurons required within the FC layer, which can be equivalent to the number of desired classes or outputs [33].

Softmax Layer

It includes the softmax activation function which is used for computing the probabilities of classification for each input image. Its representation can be given by the following equation:

$$SL_r = \frac{e^{FC_r}}{\sum_{s=1}^{mc^{l-1}} e^{FC_s}}, \quad r=1, 2, \ldots, mc^l \quad \text{............} \ 6$$

where SL_r denotes an outcome of the softmax layer [33].

Classification Layers

The utilization of this layer is so important in order to attain the ultimate determination of recognition or classification. This pivotal layer follows the winner-takes-all rule. The mathematical representation of this layer's functionality can be succinctly expressed as follows:

$$FC_r = \begin{cases} 1 & \text{if } \ SL_r = Max \\ 0 & \text{otherwise} \end{cases}, \quad r=1, 2, \ldots, mc^l \ \text{...}7$$

where FC_r denotes an output decision of the classification layer and Max denotes the obtained maximum value from the softmax layer.

Essential Feedback

The essential feedback in the DRFN architecture plays a crucial role in achieving accurate verification. In the field of verification, the DRFN adopts a one-to-one mode. In this mode, the user is required to declare their personal identity, the resulting outcome is then meticulously compared with the specific claim identity class of a user. This rigorous process culminates in a definitive outcome: either confirming or rejecting the claimed personal identity. This meticulous mode of verification ensurs that only authorized individuals are granted access. Such verification idea has also be confirmed in many reliable studies as [11,34–36] The mathematical representation of the essential DRFN feedback can be illustrated as follows:

After the training phase, DRFN stores all the weights for each fingephotos of a certain human's finger. Hence, weights representation can be enhanced as

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$\mathbf{W}^{\beta}$, where β refers to the weights of a determined human's finger ($\beta = 1,2,3,\ldots,10$). During the testing phase, if the claimed verification for the first finger ($\beta = 1$) appears to be incorrect, the β value is modified to ($\beta = 2$), corresponding to the weights for the second finger and at the same time its fingerphoto image $\mathbf{IMF}^{\beta}$ is provided at the DRFN input layer. Such process carries out for each human's finger and stops when the verification is confirmed.

This well-organized approach not only enhances data processing efficiency but also empowers the network to detect subtle patterns and features, leading to reliable and robust verification results. Such verification process holds great significance in fingerphotos recognition.

Results and Discussion

Here, basic parameters and considerations are highlighted. Then, proposed results are discussed. That is, the acquired FITF dataset will firstly be described, and DRFN Parameters and Utilities will secondly be illustrated. In addition, results and discussions will be provided.

Acquired FITF Dataset

In this study, Fingerphoto Images of Ten Fingers (FITF) dataset is acquired. It has a big number of fingerphoto images, each of them is of type RBG (colored) and of format Joint Photographic experts Group (JPG). This dataset comprises of fingerphoto images that are acquired or collected from 100 humans, ranging in ages from 16 to 75 years. Those humans or participants are partitioned into 58 males and 42 females, resulting in approximate balanced representation genders. For each participant, 10 finger photes of all fingers, in both right and left hands, are captured. This provides total of 10000 fingerphoto images in the FITF dateset. The overall size of the raw dataset has reached to 18.8 GB. Simple white background and different rotation angles have been considered during the aquiring process.

Proposed DRFN Parameters and Utilities

This section describes the DRFN system's method for biometric verification, processing fingerphoto images in sequence from submission to verification result. Any person who enrolled in the biometric system of DRFN has to provide his/her class number in order to achieve the verification. The DRFN firstly accepts a fingerphoto image of the little finger of a one hand and check the output class. If the output class appears not correspond to the class number claim, the essential feedback switches to the weights of another finger (the ring finger of the same hand). Subsequently, the DRFN inputs a fingerphoto image of the ring finger and check for the verification again. Such processes are repeated for all fingers of the first hand, then, moves to the fingers of the second hand. The remaining fingers are sequentially input and the verification process is carried out with the same policy. From this point, it can be noticed that any of the 10 fingers can confirm the verification where the claimed output class is correct.

On the other hand, this accuracy may be decreased if not all 10 fingers of both hands are used for each participant. That is, if fingerphoto images of only few fingers are utilized, it is more likely that the accuracy is reduced accordingly.

The parameters of the DRFN model are set as: 224 × 224 × 3 pixels for the input size of a fingerphoto image, 3 × 3 pixels for the convolution layer filter size, 16 filters for the number of filters in the convolution layer, the stride value is 1 × 1 pixel , zero-padding that ensures a convolution channel size has the same input channel size, maximum type for the pooling layer, 2 × 2 pixels for the filter size of the pooling layer, 2 × 2 pixels for the horizontal and vertical strides in the pooling layer, and 100 classes for the last layers (FC, SoftMax and classification).

All executions have been explored by MATLAB (version R2023b) with the computer specifications of: HP laptop equipped with an Intel Core i7-7600U processor operating at the speed of 2.90 GHz and 16 GB of computer memory.

Training Results

The suggested training phase has been carried out by employing a subset of 8000 fingerphoto images from

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the FITF dataset. Training configuration has encompassed several crucial parameters. To attain a controlled rate of adjustment DRFN parameters, a learning rate of 0.0001 has been used.

Training procedure extended over a maximum of 300 epochs. This to ensure that training is finalized in a stable and generalized representation of input-to-output data. Batch size of 32 has been utilized. This parameter determines the number of samples processed in a single forward and backward pass in the network. A balanced mini-batch size strikes a balance between gradient accuracy and computational efficiency.

The collective configuration of these parameters can achieve an optimal equilibrium between speed of convergence, stability and computational efficiency. Fig. 5 and Fig. 6 provide visual samples of training representations for index and middle fingerphoto images of left hands and right hand respectevely. These figures serve to illustrate measurements of accuracies and loss errors observed in mini-batches throughout training iterations.

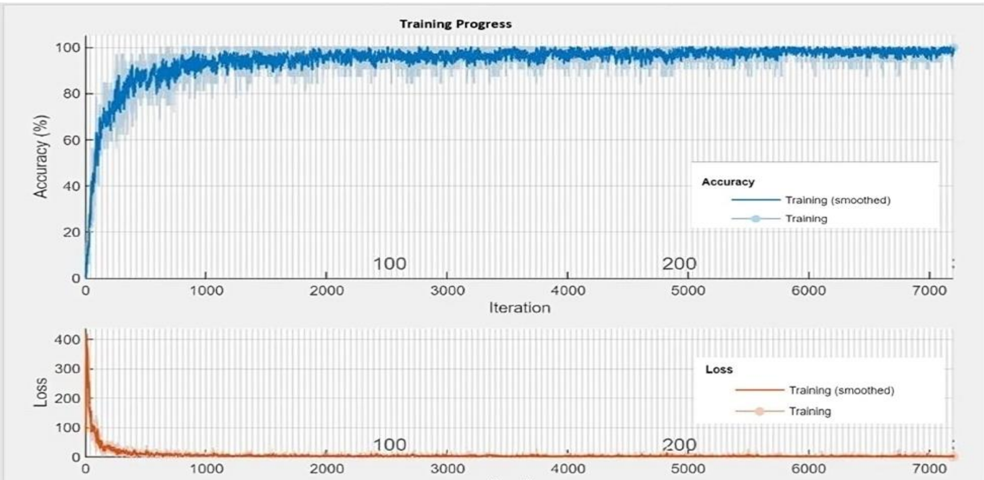

Figure 5. Training progress (accuracy and loss) for left hand index fingerphotos.

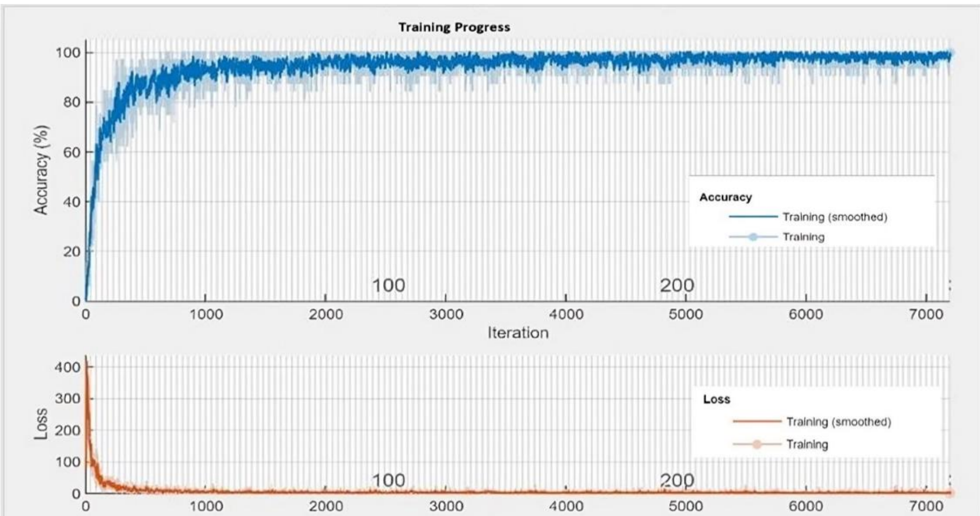

Figure 6. Training progress (accuracy and loss) for right hand middle fingerphotos.

The curves in Fig. 4 and Fig. 5 demonstrate the progress of training, specifically with regards to the accuracy and loss. It is worth noting that the accuracy improves while the loss decreases to a reasonable extent throughout the training process. At the end of training, the accuracy has reached a high value level and the loss has reached to a low value. Such demonstrations yield that acceptabale trainings are obtained.

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Testing Results

Firstly, a total of 2000 fingerphot images from the FITF dataset have been utilized. Each testing of single fingers is conducted with a feedforward DRFN model (without the essential feedback), this would provide valuable comparisons. Then, testing of all fingers is afford for the proposed completed DRFN model.

Details on evaluation parameters can be illustrated as follows:

1. False Acceptance Rate (FAR): it signifies the rate at which the biometric system mistakenly grants access to impostors. FAR can be calculated as represented in the following equation:

$$FAR = \frac{Number\ of\ impostors\ accepted}{Total\ number\ of\ impostor\ attempts} \quad .... \quad 8$$

2. False Rejection Rate (FRR): it refers to the frequency at which the biometric system erroneously denies access to genuine users. It can mathematically be expressed as following:

$$FRR = \frac{Number\ of\ genuine\ users\ rejected}{Total\ number\ of\ genuine\ users} \quad .... \quad 9$$

3. Equal Error Rate (EER): it is an essential measurement. It is a point where the FAR and FRR are equivalent. It can be expressed as follows:

$$EER = \frac{FAR+FRR}{2} \quad .... \quad 10$$

It is of utmost importance to minimize both FAR and FRR. The EER is focused here alongside with the accuracy. Obtained accuracies and EERs of humans verifications based on fingerphotos are presented in Table 1.

Table 1. Obtained testing accuracies and EERs of humans verifications based on fingerphotos

Network Model	Considered Hand	Employed Finger(S)	Accurcy	EER
Feedforward DRFN Model (Without The Essential Feedback)	Left Hand	Little Finger	93.50%	6.5 %
		Ring finger	93.0%	7.0 %
		Middle finger	92.5%	7.5%
		Index finger	93.0%	7.0 %
		Thumb	94.5%	5.5 %
	Right hand	Little finger	91.5 %	8.5 %
		Ring finger	95.5 %	4.5 %
		Middle finger	95.5%	4.5 %
		Index finger	91.6 %	8.4 %
		Thumb	92.5 %	7.5 %
			Average Accurcy	**Average EER**
Proposed Completed DRFN	Right and left hands	All fingers	99.84 %	0.16 %

From the analysis shown in Table 1, it becomes apparent that the verification accuracy achieved by the feedforward DRFN model (without the essential feedback) for left hand fingerphotos on average is 93.3%. This signifies that the level of Equal Error Rate (EER) encountered is 6.7%. In addition, the same DRFN model has achieved a verification accuracy of 93.32% for right fingerphotos images on average, with a corresponding benchmarked Equal Error Rate (EER) of 6.68%. When the proposed completed DRFN model is considered, overall results indicate a 99.84 % accuracy and the Equal Error Rate (EER) becomes 0.16 %.

Based on obtained outcomes, it can be yield that fingerphotos of any finger can serve for personal verification. Furthermore, fingerphotos of all fingers have demonstrated approximate performances, further solidifying their potential to be effectively employed in a verification system. Finally, it can be reported the proposed DRFN approach (completed DRFN model) can achieve the highest testing performances of accuracy and Equal Error Rate (EER) as it considers all human's fingers for verification.

Conclusion

In this study, we have introduced a new dataset of fingerphotos known as the FITF. This dataset encompasses extensive collection of fingerphoto images for all participants' fingers of both left and right hands. Additionally, a DRL model referred to as the DRFN has been proposed for the purpose of verifying humans by utilizing their fingerphotos. It consists of multi-layers (input, convolution, ReLU, pooling, FC, softmax, and classification layers) and essential feedback. The proposed DRL-based system (DRFN) leverages fingerphoto images of all human's fingers, sequentially.

A big number of fingerphoto images has been considered in the FITF dataset, where 10000 fingerphotos are existed (10 images for each finger from 100 participants). The DRFN approach with the FITF dataset has yielded remarkable performances for the case of personal verification. The obtained results are highly noteworthy as the remarkable accuracy of 99.84% and Equal Error Rate (EER) of 0.16% have been recorded.

Valuable comparisons are also considered between the DRL of DRFN and deep learning of DRFN without the essential feedback. For the DRFN with the absence of essential feedback, accuracies averaging of 93.3% and 93.32% have been reported for fingerphotoes of left hands and right hands, respectively. Furthermore, averaging Equal Error Rate (EER) of 6.7% and 6.68% have been reported for fingerphotoes of left hands and right hands, respectively. Still the full DRFN, with using the essential feedback, has recorded the best accuracy and Equal Error Rate (EER).
For future studies, it can be valuable to further investigate the fingerphotos regarding spoofing, vulnerability, susceptibility, mitigation strategies and liveness detections. Some relevant work can be suggested such as applying the DRFN to other biometrics. Examples of these biometrics are: finger inner knuckles, fingernail-beds and Finger Textures (FTs).

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.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at Kirsehir Ahi Evran University, Turkey.

Authors' Contribution Statement

I.N.A., M.A.Y. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

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التحقق من البشر بواسطة تبني شبكة تعلم عميق لصور بصمات الاصابع

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الخلاصة

يمكن اعتبار صورة الإصبع واحدة من أحدث وأكثر التقنيات البيومترية إثارة للاهتمام. يعني ذلك ببساطة صورة بصمة أصبع يتم الحصول عليها عن طريق هاتف ذكي بطريقة لا تتطلب الاتصال المباشر. يقترح هذا البحث نهجًا جديدًا للتحقق من البشر استنادًا إلى صورة الإصبع الفوتوغرافية. يُطلق عليه اسم شبكة الإصبع الفوتوغرافية العميقة المتكررة. تتألف من طبقة الإدخال، وسلسلة من الطبقات الخفية، وطبقة الإخراج والتغذية العكسية الاساسية. يعتمد هذا البحث على اخذ صور فوتوغرافية لكافة الاصابع الشخصية بشكل متسلسل. و يتمتع النظام بالقدرة على التبديل بين أوزان كل إصبع فوتوغرافي فردي وتوفير التحقق. تم انشاء قاعدة بينات من عدد كبير من صور الأصابع الفوتوغرافية، وتم تنظيمها وتقسيمها واستخدامها كمجموعة بيانات مفيدة في هذا البحث. تم التوصل الى نتائج عالية في الدقة في التحقق الشخصي عن طريق استخدام الصور الفوتوغرافية للاصابع.

الكلمات المفتاحية: التعرف البيومتري، التعلم العميق، صور الأصابع، التعرف الشخصي، التحقق.