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Utilizing Fingerphotos with Deep Learning Techniques to Recognize Individuals

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ABSTRACT

Biometrics based personal verification for mobile phone devices are currently well-known. In this study, a verification approach is suggested depending on fingerphoto pictures. Couple of Deep Fingerphotos Learning (CDFL) approach is proposed, where two Deep Learning (DL) networks are involved. A fingerphoto picture of the index finger is verified using the first DL network. To recognize a fingerphoto picture of a middle finger, another DL network is used. Then, the outputs of the two networks are integrated. Fingerphoto pictures from the IIITD smartphone fingerphoto dataset are used in this work. The results yield that the accuracy of the first DL network is reported as 76.95% and the accuracy of the second DL network is reported as 86.33%. Whereas, the overall accuracy of the proposed CDFL method after integrating both DL networks is benchmarked as 96.48%.

Introduction

Each finger has a variety of characteristics as the fingerprint, which is the most widely used biometric [1]. Finger Veins (FV) [2], Finger Geometry (FG) [3], Finger Inner Knuckle (FIK) [4], Finger Nail-bed (FN) [5], Finger Outer Knuckle (FOK) [6] and Finger Texture (FT) [7] other types of finger characteristics.

Important considerations have been given to fingerphotos [8]. A fingerphoto picture can be defined as a photograph of a finger that is taken using the camera of a smartphone [9]. It includes a lot of important features such as the FT features and fingerprint. The fingerphoto could be used to verify an individual's identity. Figure 1 presents a sample of a fingerphoto picture from the IIITD database which is collected from a smart phone.

Figure 1. Sample from the IIITD database for a Fingerphoto picture [10].

This paper aims to use fingerphoto pictures for recognizing humans. The work's contribution is represented by the suggested CDFL technique. It involves a couple of DL networks.

Related Work

Stein et al. offered Anti-spoofing as well as fingerphoto recognition schemes. Mobile phones were used to capture fingerphoto pictures. For each participant, just the right and left index fingers were obtained. The procedures of recognition were based on the details of the features. The median-filter feature extraction, adaptive threshold, and kernel of size 3x3 pixels were used. Then, information in binary were reached [11].

Sankaran *et al.* illustrated a fingerphoto verification method. The right middle and index fingers were employed in this experiment. Fingerphoto dataset was recognized and called the IIITD smartphone fingerphoto dataset [12]. The fingerphoto picture was primarily improved as it was converted to grayscale using the median filter, Histogram equalization and sharpening. For the feature extraction, a Scattering Networks (ScatNet) process was chosen. General minutiae have been attaineded and all remaining FT features lost their micro-textures [10].

Malhotra *et al.* applied similar ScatNet process for the feature extraction to the same dataset [21], as this may be expressed as a developed study. Nevertheless, an additional improvement method depending upon the Local Binary Pattern (LBP) was offered. As previously mentioned, the ScatNet process can acquire the global minutiae. Whereas, the remaining features, like micro-textures, were eliminated [9].

Deb *et al.* provides Android apps for obtaining the ridges of fingerphoto pictures. Both index and thumb fingers of the right and left hands were used. After analyzing each finger, three fusion approaches were used: a combination between two thumb fingers or combination between two index fingers; a combination between index and thumb fingers of each hand; and combination of all fingers (index and thumb of the two hands). For all fusions, adding rules of Score level groupings were employed [13].

Wasnik *et al.* [8] and Wasnik *et al.* [14] Video frames of finger pictures were captured with a smartphone. fingers pictures were acquired using mobile software. Wasnik et al. demonstrated a unique method for extracting features. The approach was shown to be beneficial for ridges, particularly in smartphone applications that recognize fingerphotos. The authors looked at ten different sigma values before considering the picture's largest pixel values [8]. Wasnik *et al.* presented basis comparison study for a mobile phone application of the fingerphoto recognition. Three different feature extraction processes were explored: the Binarized Statistical Picture Features (BSIF), Histogram of Oriented Gradients (HOG) and LBP. The three feature extractions were compared to Commercial-Off-The-Shelf (COTS). Other feature extractions were outperformed by the COTS. As a result, it was recommended to use pre-processing which had been established rather than practical applications [14].

Moreover, Weissenfeld *et al.* gave a demonstration of a verification work on the concept of border control requests. A hand-held device has been suggested for obtaining finger and facial pictures called Mobile Pass. The experiments that were supported were carried out using the right and left index fingers. The evaluation was conducted using a couple of LG G5 850 and HuaweiP9 mobile phones. It was suggested that employing all four fingers could improve the performance, but there were no descriptions for this. Other evaluations were carried out with the help of planned handheld equipment. This equipment was provided to collect facial and fingerphoto pictures on the Romanian-Moldavian border. Only the left and right index fingers are used. Using the four fingers with the face picture still requires extra effort [15].

Fingerphoto pictures were used for recognition in previous studies, according to the findings. Great efforts have been made to determine the best feature extraction. In this paper, relevant feature extractions are provided by using the DL . Furthermore, it has been discovered that using two fingers (middle and index) for a one hand can improve the recognition results.

Proposed Methodology

Figure 2 shows the suggested CDFL strategy's framework.

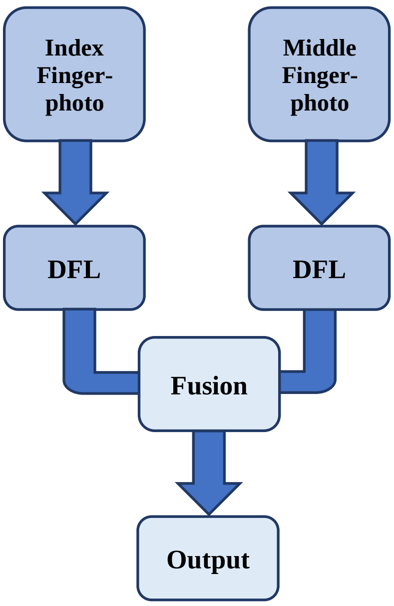

Figure 2. The suggested CDFL strategy's framework.

Input Layer

For fingerphoto pictures, the input layer has been improved. It uses fingerphotos' rectangular pictures as input. Furthermore, it works with colorful pictures. Each fingerphoto picture $\boldsymbol{X}$ is divided into 3 channels: for red channel ($\boldsymbol{X}^r$), for green channel ($\boldsymbol{X}^g$) and for blue channel ($\boldsymbol{X}^b$).

Convolution Layer

There is one convolution layer in use. This layer produces features from each channel. Convolved kernel matrix with an entry channel $\boldsymbol{C}$ denotes the feature map. The weights are represented by the kernel matrix.

The kernel matrix $t_h \times t_w \times C$ and a bias. t_h and t_w are the kernel's height and width, respectively. Suppose $W^{c^l}_{i,j,c^{l-1}}$ is the parameters of the kernel, $B_c{}^l$ is the channel bias, l is the current layer and $l-1$ is the previous layer. The value $A_{u,v,c}{}^l$ of a specific pixel at (u, v) in a channel c^l and layer l could be denoted as:

$$A_{u,v,c^l} = Bc^l + \sum_{i=-t_h^l}^{t_h^l} \sum_{j=-t_w^l}^{t_w^l} \sum_{c^{l-1}=1}^{c^{l-1}} W^{c^l}_{i+t_h^l, j+t_w^l, c^{l-1}} A_{u+i,v+j,c^{l-1}} \quad (1)$$

where: $A_{u,v,c}{}^l$ is the output of a convolution layer node, $t_h^l = (t_h - 1)/2$ and $t_w^l = (t_w - 1)/$ [16].

ReLU Layer

ReLU is a function that activates. It has the ability to produce a non-linear characteristic. It adjusts to zeros the negative values as follows:

$$o_{u,v,c^l} = \max (A_{u,v,c^l},) \quad (2)$$

where: o_{u,v,c^l} is an output of a ReLU node, and max is the process of maximum [17].

Pooling Layer

The pooling layer decreases the ReLU channels. Vast computations are usually applied in this layer. That is to say, the highest values from preceding channels are retained. The maximum pooling technique is revealed in the following equation.:

$$q_{a^l,b^l,c} = \max_{0\le a<p_h, 0\le b<p_w} o_{a^l\times p_h+a, b^l\times p_w+b,c} \quad (3)$$

where: $q_{a^l,b^l,c}$ is the output of a pooling, $0 \le a^l < p_h^l$, p_h^l is the channel's pooled height, $0 \le a^l < p_w^l$, p_w^l is the width of the pooled channel, $0 \le c < C^l = C^{l-1}$, p_h is the sub-height channel's at which pooling is required and p_w is the sub-channel width that required the pooling [18].

FC Layer

This layer adjusts for the amount of recognizing subjects and pooling nodes. Can be produced layer $l-1$ are represented as $m_1^{l-1} \times m_2^{l-1} \times m_3^{l-1}$ dimensional vectors as in to the following equation:

$$g_r = \sum_{a=1}^{m_1^{l-1}} \sum_{b=1}^{m_2^{l-1}} \sum_{c=1}^{m_3^{l-1}} W^l_{a,b,c,d,r} (Q_c)_{a,b}, \quad \forall 1 \le r \le m^l \quad (4)$$

where: g_r FC node's output, m_1^{l-1} is the previous layer's channel height, m_2^{l-1} is the previous layer channel's width, m_3^{l-1} is the number of channels from the preceding layer, $W^l_{a,b,c,d,r}$ is the weight of links between the pooling and FC layers, Qc are the vectors that represent the results of the pooling layer, and m^l is the total number of subjects that can be classified [19].

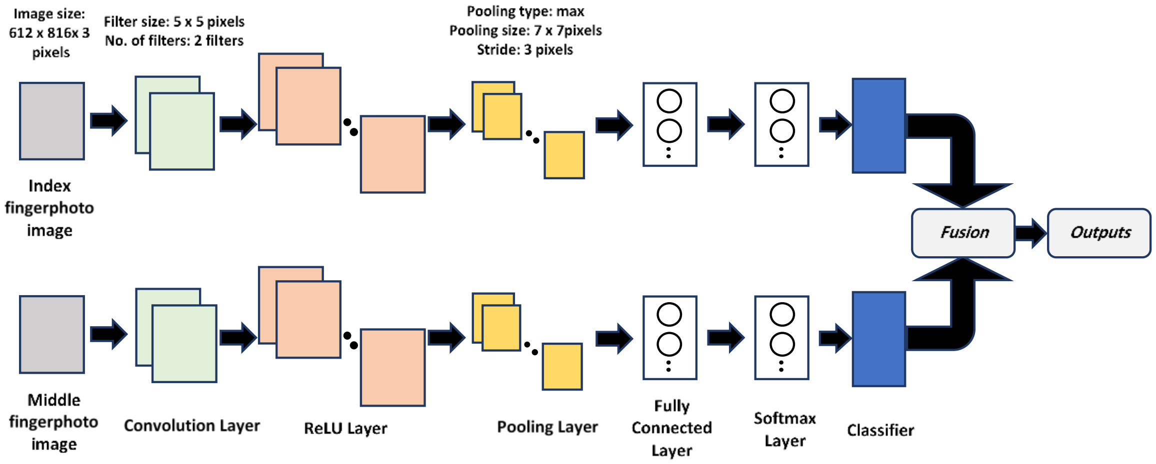

Figure 3. The CDFL approach that has been suggest.

Softmax Layer

When computing the probabilities between each output class and the input, the Softmax activation function is used. It uses the following formula:

$$O_r = \frac{\exp(g_r)}{\sum_{s=1}^{m^{l-1}} \exp(g_s)} \qquad (5)$$

where: O_r is the Softmax output [19].

Classification Layer

The decision was made using the classification layer. This layer operates on a winner-take-all basis which could be expressed as follows:

$$F_r = \begin{cases} 1 & if \;\; O_r = max \\ 0 & otherwise \end{cases}, \quad r = 1,2,3,\dots n \qquad (6)$$

where: F_r is the classification node's production decision, max refers to the highest possible value and n is the total number of classes [20].

Combination (Fusion)

Between the two DFL networks, a couple of fusions are proposed and achieved. A network is created for each fingure. In this case, the index and middle fingers are used. Inputs consist of fingerphotos. The OR rule is used to combine the outputs of the two DFL networks.

See Figure 3. The suggested CDFL is tested and implemented.

Results and Discussions

The proposed CDFL has been tested and used satisfactorily. It has achieved amazing results. Employed fingerphoto dataset and obtained results will be provided next.

IIITD Smartphone Fingerphoto Dataset

A smartphone Fingerphoto pictures has been obtained from IIITD database. The auto-focus was turned on, while, the flash was switched off during the acquiring time. In this dataset, different backgrounds and lighting conditions were utilized for collecting fingerphoto pictures. The total of participants‘ pictures were from 64 subjects, 8 pictures were taken for each of the right hand's middle and index fingers [10].

Indoor photos with natural backgrounds from the same dataset were employed in this study. Total number of participants are 64 subjects. Total number of utilized fingerphoto pictures are 1024. Both the index and middle fingers have 512 fingerphoto pictures for learning. Similarly, both the middle and index fingers have 512 fingerphoto pictures for testing. In other words, number of images in training and testing is considered as 50% each, following [20][21][23].

Results with Discussions

A practical Part is carried out on a computer with the following specifications: a Dell laptop with a Core-i7 microprocessor running at 2.7GHz and 16 MegaBytes of RAM.

The following are the characteristics of each DFL network:

(1) Size of input picture 612×816×3 pixels.
(2) Convolution layer with a filter size of 5×5 pixels.
(3) Several filters of 2 for the convolution layer.
(4) Maximum pooling of the window size 7×7 pixels.
(5) Pooling stride value of 3 pixels.
(6) Number of classes of 64.

Both DFL networks are trained by using fingerphotos with the following parameters:

(1) Adam (adaptive moment estimation) optimizer.
(2) Initial learn the rate = 0.0001.
(3) Maximum epochs = 100.
(4) Denominator offset = 10^{-8}.
(5) Squared gradient moving average decay rate = 0.999.
(6) Decay rate of gradient moving average = 0.9.
(7) Figure 4 depicts index fingerphoto picture training curves. Figure 5 depicts a middle finger picture training curves.

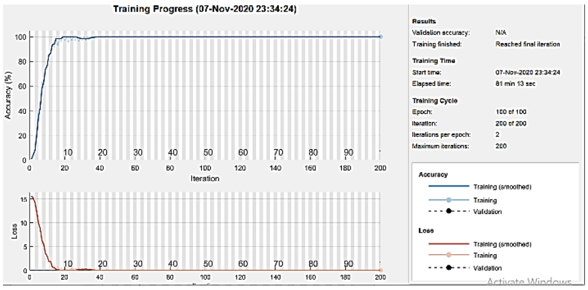

Figure 4. Learning curves for index fingerphoto pictures with 100 iterations.

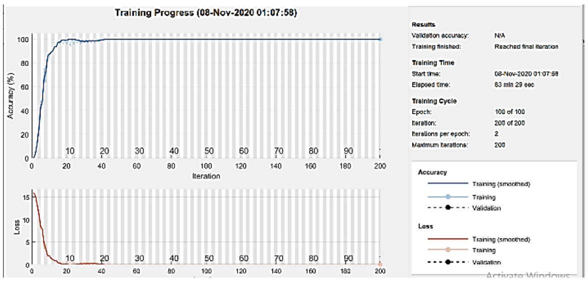

Figure 5. Learning curves for middle fingerphoto pictures with 100 iteration.

In each figure, there are two curves. One of them illustrates the relationship between the successful presision and the training iterations, and the other presents the relationship between mini-batch loss and the training iterations. The success of training is indicated by all curves. Additional results of training times can be seen in Figures 4 and 5. That is, the overall training time for the DL of the index fingerphoto pictures is 81 minutes and 13 seconds. Furthermore, the overall training time for the DL of the middle fingerphoto pictures is 83 minutes and 29 seconds. Obviously, both times are near from each other. This means that index fingerphoto pictures and middle fingerphoto pictures require close processing times if they be under the same conditions.

In practice, the DFL networks have been investigated using fingerphoto pictures for testing. The attained results are promising. That is, the first DL network that is designed for the index fingerphoto pictures achieved a successful accuracy equal to 76.95% and a low Equal Error Rate (EER) equal to 23.05%. The middle fingerphoto pictures which were assigned to the second DL network had a successful accuracy equal to 86.33% percent and an EER equal to 13.67%.

When implementing the fusion between the outputs of both networks by utilizing the OR rule, very high accuracy of 96.48% has been achieved and a very low EER of 2.34% has been benchmarked. The overall framework is named the CDFL, as mentioned. Table 1 demonstrates the reported testing results.

Table 1. The reported testing results.

Method	Accuracy	EER
DFL (for index fingerphoto pictures)	76.95%	23.05%
DFL (for middle fingerphoto pictures)	86.33%	13.67%
CDFL Approach	96.48%	3.52%

Comparisons

Other methods that consider fingerphoto regions are utilized for comparisons. Table 2 shows such comparisons.

Table 2. Comparisons with methods that consider fingerphoto regions.

Reference	Method	Accuracy	EER
Kanhangad *et al.* [21]	CompCode +Matching	94%	6%
Al-Nima *et al.* [22]	IFE (bell-shaped histogram)+PNN	87.34%	12.66%
	IFE (flat histogram)+PNN	94.46%	5.54%
	IFE (exponential histogram)+PNN	94.58%	5.42%
Our Approach	CDFL	96.48%	3.52%

In this table, it can be seen that the method of Competitive Coding (CompCode) and matching recorded the EER of 6% (accuracy equal to 94%) in [21]. The methods of Image Feature Enhancement (IFE) with bell-shaped histogram and Probabilistic Neural Network (PNN), IFE with flat histogram and PNN, and IFE with exponential histogram and PNN respectively reported the EERs of 12.66%, 5.54% and 5.42% (accuracies equal to 87.34%, 94.46% and 94.58%) in [22]. Our method of the CDFL approach has benchmarked the EER of 3.52% (accuracy equal to 96.48%). It can be mentioned that a method based on the DL may attain higher performances than other compositional methods.

Conclusion

In this paper, the suggested method of a couple of figurinephoto picture recognition depending on fingerphoto pictures.

CDFL approach was suggested and implemented. It contained two DFL networks. One for index fingerphoto pictures and another one for middle fingerphoto pictures. The outcomes of both DFL networks were fused together.

IIITD smart phone fingerphoto dataset was employed to evaluate the recognition methods. Successful accuracies of 76.95%, 86.33%, and 96.48% were achieved for the DFL network of index fingerphoto pictures, DFL network of middle fingerphoto pictures, and CDFL, respectively. The last result for the CDFL is excellent and remarkable.

Competing Interests

The authors declare that there is no competing of interest.

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