



## Deep Convolutional Neural Network for Finger-knuckle-print Recognition

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### ABSTRACT

Finger-Knuckle-Print (FKP) is an accurate and reliable biometric in compare to other hand-based biometrics like fingerprint because of the finger's dorsal region is not exposed to surfaces. In this paper, a simple end-to-end method based on Convolutional Neural Network (CNN) is proposed for FKP recognition. The proposed model is composed only of three convolutional layers and two fully connected layers. The number of trainable parameters hereby has significantly reduced. Additionally, a straightforward method is utilized for data augmentation in this paper. The performance of the proposed network is evaluated on Poly-U FKP dataset based on 10-fold cross-validation. The best recognition accuracy, mean accuracy and standard deviation are 99.83%, 99.18%, and 0.76, respectively. Experimental results show that the proposed method outperforms the state-of-the-arts in terms of recognition accuracy and the number of trainable parameters. Also, in compare to four fine-tuned CNN models including AlexNet, VGG16, ResNet34, and GoogleNet, the proposed simple method achieved higher performance in terms of recognition accuracy and the numbers of trainable parameters and training time.

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## 1. INTRODUCTION<sup>1</sup>

Using a reliable recognition method is a critical challenge in both academic and industrial contexts [1]. Biometrics can be defined as unique behavioral or physical characteristics of humans. Given the convenience and accuracy of biometric-based methods, they have huge potentials in diverse applications such as e-marketing, security, access control, e-banking, etc. [1]. In the past decades, many studies have investigated the advantages of some biometric characteristics, including face [2], iris [3], fingerprint [4], palm-print [5], hand geometry [6], finger-vein [7], and Finger Knuckle Print (FKP) [8]. Compared to different types of biometrics, hand-based biometrics has received significant attention in recent years [1].

Recent studies show that skin wrinkles on the outer area of finger knuckle have a unique pattern. Due to the unique features of FKP, it can be used as a discriminative

biometric method [9]. FKP has several advantages over other hand-based biometrics. For example, people tend to grasp stuff by the inner side of their hands, so the FKP surface is not damaged or abraded. Since the data collection process in the FKP is contactless, it is usually more popular among users [10]. In this article, attempts have been made to design a simple method based on Convolutional Neural Network (CNN) for FKP recognition.

To the best of our knowledge, despite the excellent performance of CNN in different computer vision applications, the use of CNN models for the recognition of FKP image has received scant scholarly attention. Therefore, this study uses a novel CNN model to recognize FKP image. The main points of this work are as follows:

1. To the best of our knowledge, this is the first work that focuses on the effectiveness of CNN model for FKP recognition.

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2. A simple end-to-end learning method is proposed without the need of handcrafted feature extraction for recognizing FKP images.
3. A straightforward data augmentation approach is utilized to collect appropriate data for training proposed CNN model.
4. As an investigation, four well-known CNN architectures including VGG16 [11], Google-Net [12], and ResNet34 [13], and AlexNet [14] are fine-tuned for FKP recognition.

The rest of this article is formed as follows. Section 2 reviews the major works in FKP recognition. Section 3 describes the proposed methodology. The details of experimental results are presented in section 4. Discussion and comparison are explained in section 5. Finally, conclusions and future works are explained in section 6.

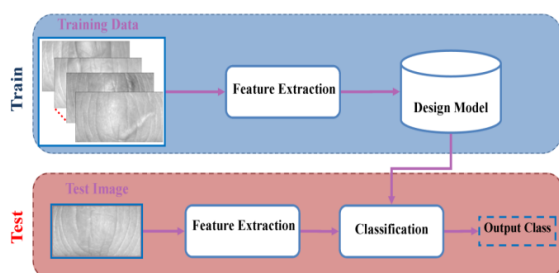
## 2. LITERATURE REVIEW

Due to the importance of FKP in user recognition, many researchers have conducted extensive studies on the FKP recognition. To the best of our knowledge, all state-of-the-art in FKP recognition can be assigned to two main categories: classic and deep-based approaches. As shown in Figure 1, studies in both categories comprise almost two parts feature extraction and classification. As the features are extracted manually in the classic works, deep-based methods extract appropriate features automatically. In the following, the most seminal works in both categories are reviewed.

Woodard and Flynn [15], one of the first researchers to investigate the surface of finger knuckle as a biometric identifier, designed a dataset contain 3D finger back knuckle surface with the Minolta 900/910 sensor. Then, they used a curvature-based shape indicator for extracting desired features. Kumar and Ravikanth [10] presented a person identification system based on a 2D finger-back surface. They applied several approaches like PCA, LDA, and ICA to extract feature. Kumar and Zhou [16] applied the Robust Line Orientation Code to the FKP images for extracting the local orientation information as feature vectors. Zhang et al. [17] applied

the Gabor filter for extracting the magnitude and orientation information of FKP images. Zhang et al. [18] have applied the Fourier Transform (FT) to the FKP images, and the FT coefficient was considered as a feature representation. Morales et al. [19] utilized the Gabor filter for enhancing the FKP lines, adopting SIFT descriptor for the feature extraction. Zhu [20] utilized SURF descriptor to extract features and then matching. Badrinath et al. [21] combined SURF and SIFT to enhance the FKP texture images, and FKP recognition. The reflectance and illumination were extracted from each FKP image [22]. Then they used serial feature fusion to create a huge vector of feature for each individual. The Gabor filter was utilized for extracting desired features [8]. They also used Hamming distance along with Support Vector Machine (SVM) for reducing False Acceptance Rate (FAR). Vidhyapriya and Lovelyn Rose [23] used the Gabor filter and Expectation-Maximization (EM) to extract texture patterns. They also utilized SIFT descriptor to create a feature vector. Heidari and Chalechale [24] have extracted the features by a pattern histogram based on entropy and some statistical texture features. Then, the genetic algorithm was used to extract the optimized sub-features. Attia et al. [25] used Multilayer Deep Rule Based (DRB) method for FKP recognition. First, two types of features including Binarized Statistical Image feature and Gabor Filter bank are extracted from input images. These features are then fed to fuzzy rule based DRB classifier for person authentication. Chlaoua et al. [26] used PCA-Net beside SVM for FKP recognition. They applied PCA to extract two feature banks and SVM for classification. Even though these works were impressive, but the features are extracted manually. Unlike classical works, features are extracted automatically in deep-based methods. CNN is the most significant models in deep-based works. Thus, in the second category, the CNN models were used for FKP recognition.

LeCun and Bengio [27] were the first to propose CNN architecture. CNN models have been the subject of considerable attention in most computer vision applications [28-31]. These families of neural networks, which combine feature extraction and classification roles, are intended to recognize images based on their scale, shift, and distortions. Generally, CNNs contain input and output layers as well as several sequentially-connected convolutional layers that are followed by a fully connected layer(s). In each convolutional layer, inputs of the previous layer are convolved with trainable filters. Relu used as an usual activation function in CNN layers [32]. To diminish data size and reduce the overfitting phenomena [33], the pooling operation was performed for the output of the current layer. Irrespective of the great performance of CNN models in diverse computer visions, the utilization of CNN models for the recognition of FKP images has been largely overlooked.



**Figure 1.** General diagram for the FKP recognition

As far as we are concerned there are studies [34, 35] that utilized CNN models for recognizing FKP images. In this paper, we address the FKP recognition issue and attempt to develop a new design for the recognition of the FKP image.

### 3. PROPOSED METHODOLOGY

Despite the excellent performance of CNN in different applications in computer vision community, the use of CNN models to recognize FKP image has been a low research priority. Therefore, this paper aims to propose FKP recognition by CNN models. In the following subsections, Transfer Learning (TL) and the proposed CNN architecture are reviewed for the FKP recognition.

**3.1. Transfer Learning** Providing adequate labeled training data with a distribution similar to the test data is the best scenario for machine learning [36]. However, collecting sufficient training samples is time-consuming, expensive, or even impossible in some cases [36]. TL is a research problem in machine learning that retains knowledge obtained from the solution of a problem (source domain) to be applied to different but relatively similar problems (target domain). TL has been the most popular approach in CNN models in recent years [37, 38]. In fact, few people train an entire CNN models from scratch (with random initialization), since it is usually uncommon to have a database of adequate size. Instead, it is customary to pre-train a CNN on a large dataset, e.g. Image-Net [14], and then utilize the CNN either as a feature extractor or an initialization for the desired task. Fine-tuning is the most common approach in the TL scenarios. In this approach, some earlier layers are frozen (due to over-fitting concerns), and the network is re-trained by further layers. This is inspired by the observation that the CNN's earlier features include more typical features (e.g. edge detectors), which are common features in numerous tasks; however, further layers become gradually more specific to the details of the classes contained in the original dataset.

**3.2. Proposed CNN Model For Recognizing FKP Images** As shown in Figure 2, the source and target domains are entirely different in FKP recognition. Therefore, TL-based methods may not be the best choice for FKP recognition. In this article, we presented a CNN model for FKP recognition. The proposed CNN architecture is depicted in Figure 3. As can be seen, the proposed architecture consists of one input layer, data augmentation block, three convolutional layers with two corresponding max-pooling ( $L_1$  and  $L_2$ ) and one average-pooling layers ( $L_3$ ) for feature extraction, two fully-connected layers ( $L_4$ , and  $L_5$ ) for classification, and finally one output layer. According to Figure 3, feature

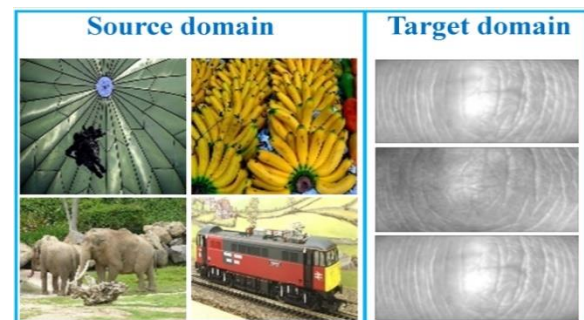
extraction and classification were conducted automatically. In the training phase, first each input image is augmented and then the CNN's trainable parameters are updated with respect to its label by specific learning algorithm. Then, in a network with adjusted parameters a feature is extracted from the input image in the test phase and in the forward path the label is predicted after classification. In the test phase, there is no data augmentation for the input image. The main goal of this model design is to achieve best performance with the adequate number of layers and weights.

### 4. EXPERIMENTAL RESULTS

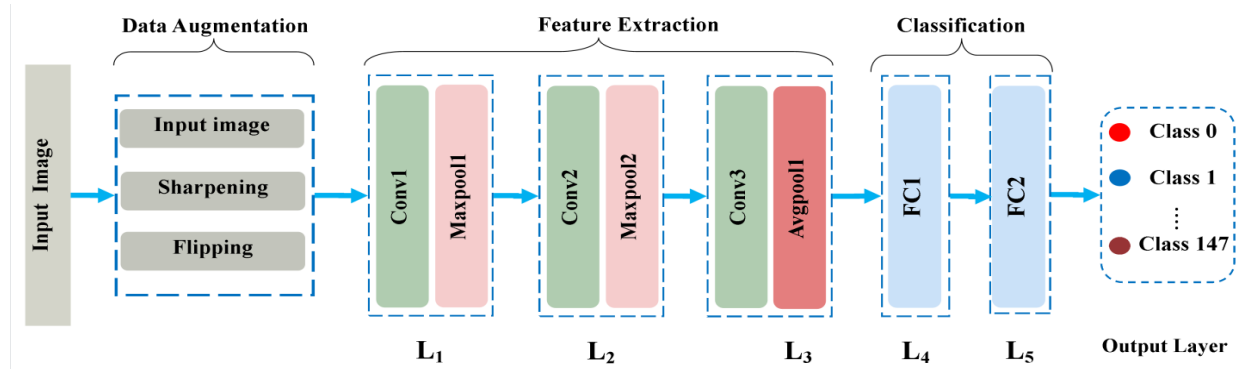
The aim goal of this article is to propose a simple CNN architecture for recognizing FKP images. All experiments were utilized by a machine with these features: Intel® core i3 - 6300 CPU @3:70GHz, 48GB RAM, and NVidia® 1060Ti 6GB GPU. The experiments were conducted using the PyTorch® framework installed on Microsoft® Windows10.

**4.1. Detail of Simulation** There are several important parameters to design the proposed CNN model such as: the kernel size, number of filters, strides, and etc. that are summarized in Table 1. Also, the proposed CNN architecture requires some hyper-parameters such as: batch sizes, initial learning rate, regularization, and number of epochs that are shown in Table 2. It should be noted all parameter values in Table 1 and also the hyper-parameter values in Table 2 have been set experimentally. Finally The back-propagation algorithm beside the Adam[39] optimizer is utilized for training the proposed CNN architecture.

**4.2. Database** For evaluating the proposed personal recognition system, the Poly-U FKP database [17] was utilized. This database was collected from 165 participants. In the data collection process, 12 samples were taken from each finger knuckle in two distinct



**Figure 2.** Some image samples in the source and target domains. As can be seen, the source and target domains are different in terms of texture, semantics, etc.



**Figure 3.** Proposed CNN model for recognizing FKP images. This architecture contains five layers (L<sub>1</sub>, L<sub>2</sub>, L<sub>3</sub>, L<sub>4</sub>, and L<sub>5</sub>) for extracting feature and classification

**TABLE 1.** The details of the proposed CNN architecture depicted in Figure 3

Layer Name	Layer Type	No. of Filters	Kernel Size	Stride	Input Features	Output Features	No. of Parameters
L <sub>1</sub>	Convolution (Conv1)	16	(3×3)	(1×1)	(1,220,110)	(16,218,108)	448
	Batch Normalization	---	---	---	(16,218,108)	(16,218,108)	32
	RELU	---	---	---	(16,218,108)	(16,218,108)	0
	Max Pooling (Maxpool1)	---	(4×4)	(4×4)	(16,218,108)	(16,54,27)	0
L <sub>2</sub>	Convolution (Conv2)	32	(3×3)	(1×1)	(16,54,27)	(32,52,25)	4,640
	Batch Normalization	---	---	---	(32,52,25)	(32,52,25)	64
	RELU	---	---	---	(32,52,25)	(32,52,25)	0
	Max Pooling (Maxpool2)	---	(2×2)	(2×2)	(32,52,25)	(32,26,12)	0
L <sub>3</sub>	Convolution (Conv3)	64	(3×3)	(1×1)	(32,26,12)	(64,24,10)	18,496
	Batch Normalization	---	---	---	(64,24,10)	(64,24,10)	128
	RELU	---	---	---	(64,24,10)	(64,24,10)	0
	Average Pooling (Avgpool1)	---	(2×2)	(2×2)	(64,24,10)	(64,2,2)	0
L <sub>4</sub>	Fully Connected (FC1)	---	---	---	256	256	65,792
	RELU	---	---	---	256	256	0
L <sub>5</sub>	Fully Connected (FC2)	---	---	---	256	148	38,036
<b>Totally = 127,636</b>							

**TABLE 2.** Hyper-parameter setting of the proposed CNN model

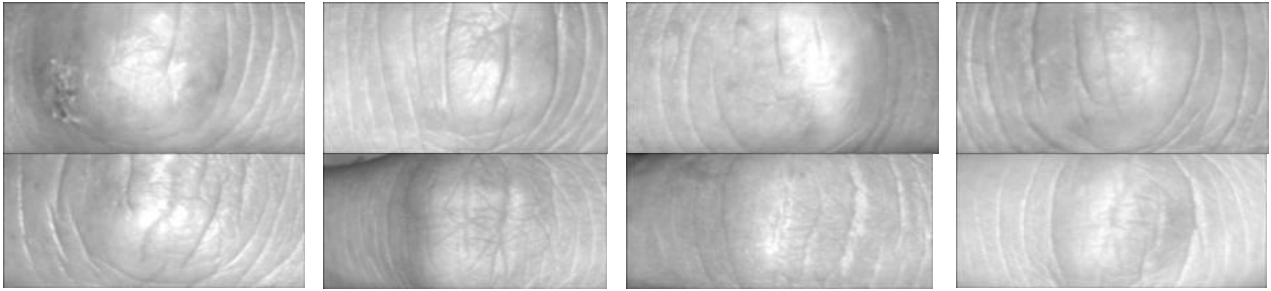
Hyper-parameter	value
Batch size	8
Number of epochs	100
Initial learning rate	0.001
L2regularization	0.001

sessions (six samples per session). In each session, the images of a participant's Right Index (RI), Right Middle (RM), Left Middle (LM), and Index (LI), fingers were

collected, respectively. A total of 7,104 samples from 592 distinct fingers were public available from 148 participants which used in this work. After data collection, the region of interest was extracted from each finger in the preprocessing. Finally, 7,104 samples (size: 220×110) were obtained. Figure 4 shows some samples from the Poly-U FKP database.

The existence of many trainable parameters is one of challenges in CNN models [36]. Thus, sufficient data is required to avoid over-fitting in training CNN models. In many real-life applications, appropriate data is not available. There are several approaches for data augmentation [40]. In this paper, two data augmentation





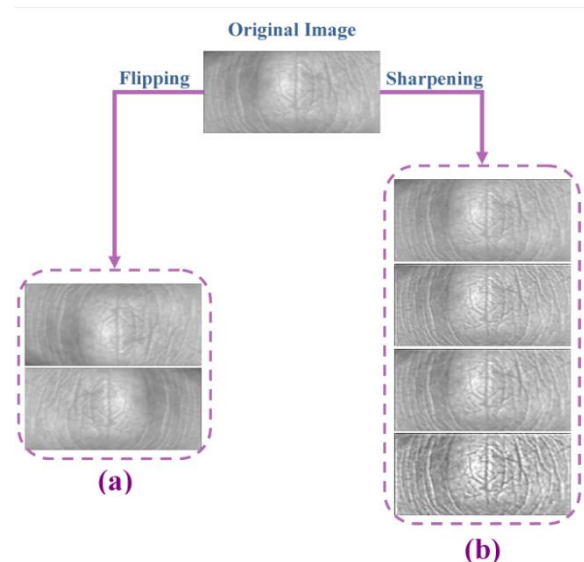
**Figure 4.** Some samples of Poly-U FKP database. Upper row, from left to right, LI, LM, RI, and RM fingers of the same person, respectively. Lower row, from left to right, four different LI fingers of different persons

methods have been employed. First, as described by Bloice et al. [41], we attempted to augment data by different zooming scales, different rotation angles and elastic distortions. In this augmenting process, 50% of data are chosen for testing in each class and remaining 50% is initially augmented by Bloice et al. [41] and then saved for the training set. Moreover, the data in each class will quadruple after the augmentation. The second approach includes simple transformations such as sharpening and flipping on the input finger image. As shown Figure 5, the Gaussian low-pass filter with four different parameter values was used for image sharpening. Image flipping was performed by flipping original the image horizontally and vertically. All of these transformations were conducted in MATLAB® 2020 after which each image sample was augmented into six new image samples. The K-fold cross validation is one of standard methods for training models, especially when limited label data are available. Thus, for first time, this paper uses 10-fold cross validation for training CNN model. In the second augmentation process, the principal 10% of data was chosen for the testing set, and remaining data (=90% of all data) was first augmented with the proposed augmentation method and then saved for the training set.

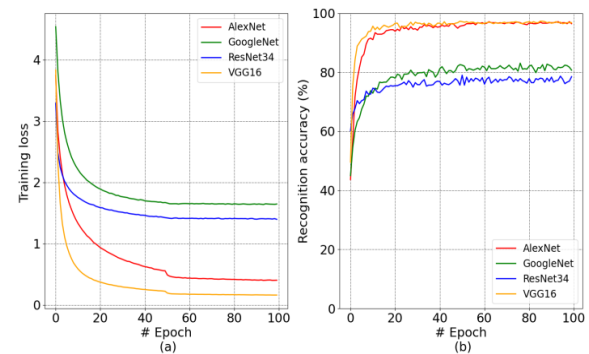
**4.3. Experiment and Evaluation** In the first, the four well-known CNN models, AlexNet, VGG16, ResNet34, and GoogleNet, which trained on Image-Net dataset, were fine-tuned for FKP recognition. To do so, the three last layers of the VGG16 and AlexNet and the last layer of two other CNNs were re-trained on the augmented FKP dataset. The recognition accuracy of the training set and the training loss of these CNN models are shown in Figure 6. As can be seen, VGG16 and AlexNet outperformed other CNN models.

As noted in the TL section, when the target and source domains have different distributions, the TL approach will be ineffective. Thus, we seek to train the proposed CNN architecture on dataset that is augmented by two approaches separately. The results of the experiment are presented in Table 3. The first augmentation method

employs a number of transformations like elastic distortion, which may deform the structure of FKP images. In contrast, the second augmentation method effectively retains the structure of images. Hence, as



**Figure 5.** Data augmentation includes: a) flipping, b) sharpening



**Figure 6.** a: Training loss, b: recognition accuracy of FKP recognition by fine-tuning the four conventional CNN models

shown in Table 3, compared to the above two augmentation methods, the proposed CNN model with the second augmentation has higher recognition accuracy. Also, Table 3 compares the efficiency of the proposed approach with four conventional CNN architectures in terms of the number of trainable, training time, and recognition accuracy. As shown in this table, the proposed CNN not only has fewer parameters but also demonstrates a higher performance. Finally, the experimental result of proposed method with second

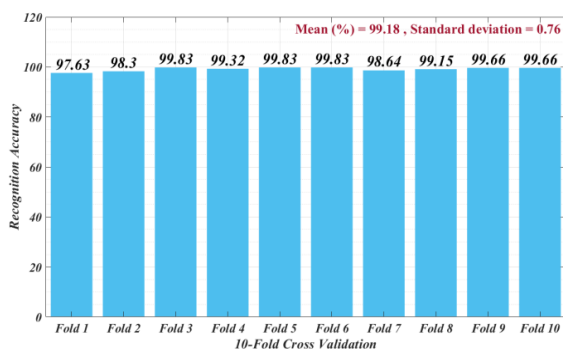
augmentation in 10-fold cross validation shown in Figure 7. Receiver Operating Characteristic (ROC) curves is great tools for evaluating the performance of a biometric system. This diagram can be plotted by drawing True Positive Rate (TPR) versus False Positive Rate (FPR) for all thresholds [24]. Figure 8 depicted the ROC of the presented approach compared to the four CNN models. As can be seen, this diagram confirms the effectiveness of the presented CNN model with second augmentation compare to four fine-tuned CNN models.

**TABLE 3.** Comparing the performance of four CNN models with the proposed

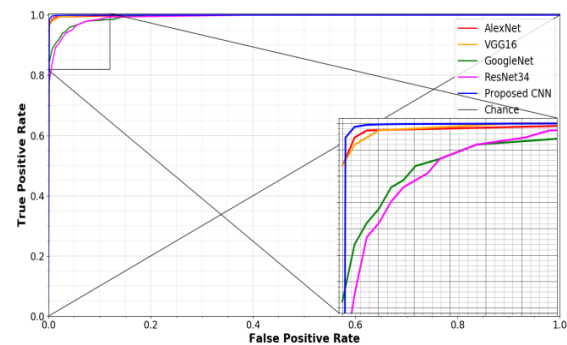
Method	#Trainable parameters	Recognition Accuracy (%)	Training Time(GPU)
ResNet34	75,924	79.02	167m
VGG-16	120,152,212	97.29	546m
GoggleNet	151,700	83.08	124m
AlexNet	55,140,500	97.12	200m
<b>Proposed CNN + first Augmentation method [41]</b>	<b>127,636</b>	<b>96.50</b>	<b>286m</b>
<b>Proposed CNN + second Augmentation method</b>	<b>127,636</b>	<b>99.83<sup>†</sup>/98.18<sup>*</sup></b>	<b>157m</b>

\*: The average recognition accuracy in 10-fold cross-validation

†: The best recognition accuracy in 10-fold cross-validation



**Figure 7.** The recognition accuracy of the proposed CNN architecture in 10-fold cross validation



**Figure 8.** The ROC of the proposed CNN architecture and four conventional CNN models

Based on two augmentation methods, Table 4 depicted the performance of proposed model for different fingers. As can be see, the proposed CNN architecture with the second augmentation method has higher recognition

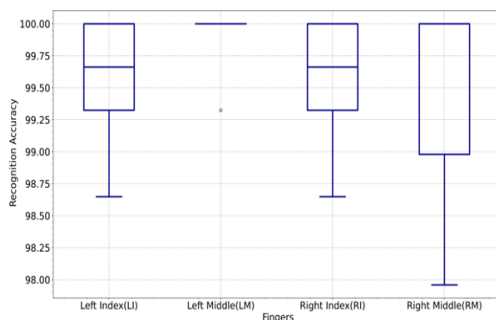
accuracy. In the last step of this experiment, the performance of the presented approach with the second augmentation was assessed for different fingers in 10-fold cross validation, as depicted in Figure 9.

**TABLE 4.** The performance of the presented approach with respect to various fingers in two different augmentation process

Method	Recognition accuracy of each finger (%)			
	LI	LM	RI	RM
Proposed CNN + first Augmentation method [41]	95.4	95.6	94.4	96.6
Proposed CNN+ second Augmentation method	99.6 <sup>†</sup> /99.3 <sup>*</sup>	100.0 <sup>†</sup> /99.8 <sup>*</sup>	100.0 <sup>†</sup> /99.5 <sup>*</sup>	100.0 <sup>†</sup> /99.5 <sup>*</sup>

\*: The average recognition accuracy in 10-fold cross-validation

†: The best recognition accuracy in 10-fold cross-validation



**Figure 9.** The performance of the proposed approach (with second augmentation) with respect to different fingers (Right Index (RI), Right Middle (RM), Left Middle (LM), and Index (LI)) in 10-fold cross validation

## 5. DISCUSSION AND COMPARISON

This section draws a comparison between our study and the most recent state-of-the-art works. The literature review suggests that the research on FKP recognition can be split into two groups, classic and deep-based methods. Unlike all classic methods in which appropriate features are extracted manually, in this paper, the feature extraction and classification are conducted automatically. As depicted in Table 5, the proposed model outperforms the classic works in term of recognition accuracy.

One of the essential challenges in the CNN model is the number of trainable parameters, which makes these

models inapplicable for low-computing devices such as mobile phones. This paper, for the first time, investigated the effectiveness of CNN model for FKP recognition and strived to propose a simple end-to-end architecture for recognizing FKP images. In addition, in this paper, a straightforward method was utilized for data augmentation. In this regard, Table 6 compares the proposed model with the latest single finger-based works.

As it is evident, our proposed method is superior to other classic works. As shown in Table 5, compared to other works in the deep-based methods the proposed CNN structure not only demonstrates competitive performance in term of recognition accuracy but also the trainable parameters reduced significantly. In fact, compared to the deep-based methods, our proposed method offers several advantages such as fewer trainable parameters, simplicity, and efficient data augmentation.

## 6. CONCLUSION AND FUTURE WORKS

Given that behaviors and attributes are unique features, human biometrics (e.g. palm-print, finger vein, hand geometry, fingerprint, and Finger Knuckle Print), can be used to improve personal validation. In this paper, attempts were made to recognize FKP using a new CNN model. In the experiments, first four CNN models, including AlexNet, VGG16, ResNet34, and GoogleNet, were fine-tuned for FKP recognition. Then, a new CNN model was developed in the second set of experiments.

**TABLE 5.** Comparing the performance of the presented approach (with second augmentation) with the state-of-the-art methods

Category	Ref.	Method	#Trainable Parameters	Database: Poly-U FKP		Recognition Accuracy (%)
				(Train%,Test%)	# of Class	
Classic	[42]	Log-Gabor + Gray Level Intensity	----	(50, 50)	165	96.56
	[43]	DFB + LDA + Norm	----	(50, 50)	165	99.29
	[44]	Differential box-counting + fractal dimension	----	N/A	165	97.29
	[45]	Gabor filter + fractal dimension	----	(50, 50)	165	93.73
	[8]	Gabor features + Support Vector Machine	----	N/A	165	89.33
	[23]	Gabor features + Expectation Maximization + SIFT	----	N/A	165	98.00
	[24]	Entropy pattern histogram + texture features	----	(60,40)	165	94.91
	[25]	Multilayer Deep Rule Based (DRB)	----	N/A	165	99.65
	[26]	PCANet + Support Vector Machine	----	N/A	165	100
	Deep	[34]	Siamese convolutional neural network model	253,000	(90, 10)	150
----		<b>Proposed CNN + first Augmentation method</b> [45]	<b>127,636</b>	<b>(50,50)</b>	<b>145</b>	<b>96.50</b>
----		<b>Proposed CNN + second Augmentation method</b>	<b>127,636</b>	<b>10-fold</b>	<b>145</b>	<b>99.83<sup>†</sup>/99.18<sup>*</sup></b>

<sup>\*</sup>: The average recognition accuracy in 10-fold cross-validation

<sup>†</sup>: The best recognition accuracy in 10-fold cross-validation

**TABLE 6.** Comparing the performance of the presented approach (with second augmentation) with respect to different fingers (RI: Right Index, and RM: Right Middle, LI: Left Index, LM: Left Middle)

Category	Ref.	#Trainable Parameters	Database: Poly-U FKP		Recognition accuracy of each finger (%)			
			(Train%, Test%)	# of Class	LI	LM	RI	RM
Classic	[42]	----	(50, 50)	165	89.9	88.5	88.4	89.4
	[43]	----	(50, 50)	165	90.3	88.6	89.7	89.7
	[22]	----	N/A	165	91.0	94.8	91.4	91.8
	[8]	----	N/A	165	97.4	97.5	94.2	99.1
	[25]	----	N/A	165	93.5	94.3	93.9	94.1
	[35]	6,985,812	(50, 50)	165	99.1	98.90	99.4	98.3
Deep	<b>Proposed CNN + first Augmentation method [41]</b>	<b>127, 636</b>	<b>(50,50)</b>	<b>145</b>	<b>95.4</b>	<b>95.6</b>	<b>94.4</b>	<b>96.6</b>
	<b>Proposed CNN + second Augmentation method</b>	<b>127, 636</b>	<b>10-fold</b>	<b>145</b>	<b>99.6<sup>†</sup>/99.3*</b>	<b>100.0<sup>†</sup>/99.8*</b>	<b>100.0<sup>†</sup>/99.5*</b>	<b>100.0<sup>†</sup>/99.5*</b>

\*: The average recognition accuracy in 10-fold cross-validation

†: The best recognition accuracy in 10-fold cross-validation

The open-source Poly-U FKP dataset was used for training and testing. Due to limited data, straightforward methods were adopted for data augmentation, which compared to other data augmentation, can effectively keep the structure of FKP images. In the TL approach, VGG16 surpasses the other three CNN models. In the subsequent experiment, the proposed CNN model outperformed four conventional CNN in terms of recognition accuracy, quantity of trainable parameters, and training time. In the last part of the experiment, the proposed CNN was compared with the latest works, with the results indicating its higher performance in term of recognition accuracy. In a future study, we intend to expand TL learning in two parallel domains. For this purpose, we will consider the fingerprint dataset as the source domain and the FKP dataset as the target domain. The proposed CNN will be trained on the fingerprint dataset and the obtained knowledge will be used for FKP.

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**Persian Abstract**

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**چکیده**

به دلیل اینکه ناحیه پشتی انگشت در معرض تماس با سطوح قرار نمی‌گیرد، در مقایسه با سایر بیومتریک‌ها مبتنی بردست، **Finger-Knuckle-Print (FKP)** یک بیومتریک دقیق و قابل اعتماد می‌باشد. در این مقاله یک روش ساده بر اساس شبکه‌های عصبی عمیق برای تشخیص **FKP** پیشنهاد شده است. روش پیشنهادی تنها از سه لایه کانولوشنی و دو لایه کاملاً متصل تشکیل شده است. به همین دلیل تعداد وزن‌های قابل آموزش به شدت کاسته شده است. همچنین یک روش سرراست برای افزودن داده در این مقاله پیشنهاد شده است. بهترین دقت، دقت متوسط و انحراف معیار روش پیشنهادی روی پایگاه داده **Poly-U FKP** و براساس **10-fold cross-validation** به ترتیب  $99.83\%$ ،  $99.18\%$  و  $0.76\%$  می‌باشد. نتایج پیاده‌سازی نشان می‌دهد که روش پیشنهادی از لحاظ دقت تشخیص و تعداد پارامترهای قابل آموزش، از روش‌های موجود بهتر عمل می‌کند. همچنین در مقایسه با شبکه‌های عصبی مانند **AlexNet**، **VGG16**، **ResNet34** و **GoogleNet** که برای تشخیص **FKP** اصلاحاً **fine-tune** شده‌اند روش ساده پیشنهادی از نظر دقت تشخیص و تعداد پارامترهای قابل آموزش و زمان آموزش عملکرد بالاتری را به ارائه می‌دهد.

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