Transfer Learning Using VGG Based on Deep Convolutional Neural Network For Finger-Knuckle-Print Recognition

Amira HAMIDI[1], Salma KHEMGANI[1] and Khaled BENSID[1]

[1]*Laboratoire de Génie Electrique Université Kasdi Merbah, Ouargla, Algeria.*

Abstract

Transfer learning is an example of Convolutional Neural Network (CNN) method. It based to reusing a pre-trained model knowledge for another task. which used for image classification, feature extraction, and clustering problems. In this paper, we used two types of the pre-trained models VGG–16 and VGG-19 with deep convolutional neural network to extract the features of Finger-Knuckle-Print FKP images in order to develop an efficient multimodal identification system. The results obtained in this work show an excellent performance for unimodal and multimodal identification systems.

Keywords

Tansfer learning, Convolutional Neural Network (CNN), VGG-16, VGG-19, finger-knuckle-print (FKP)

1. Introduction

New technologies penetrate all life areas and with our world being digitized very quickly, so the confidential information protection has become more and more important to users and organizations. For that, this topic has attracted the attention of researchers today to find a safe and effective way to protect the personal information and improve the privacy.

The automatic computer-based biometric recognition systems have been continuously replacing password-based identification approaches (classic approaches) for the last few years. Token-based methods (ID Card) can be easily stolen or lost, and information or passwords can be guessed or forgotten (pin or ID) [1]. As a result, these approaches are limited in their implementation in academic and commercial settings. In this part, physiological characteristics include biometric features derived from human biological organs such as the iris, retina, ears, and hand features...etc, whereas behavioral characteristics include gait, accent, signature, and gesture. Recently, fingerprints, Finger knuckle print, ears, iris, hand geometry, and many other characteristics have been extensively used as security features in computer laptops, voting systems, visa enrollments, cell phones, e-passports, and e-banking [2].
Finger knuckle print-based recognition systems have many advantages over common hand biometrics such as fingerprint, palm print, hand geometry, or their combinations like low-resolution

ICCSA'2021: The 2nd International Conference on Computer Science's Complex Systems and their Applications, May 25–26, 2021, Oum El Bouaghi, ALGERIA

amira.hamidi1963@gmail.com (A. HAMIDI); salma.khamgani@gmail.com (S. KHEMGANI); khaled.sid@gmail.com (K. BENSID)

imaging is possible and provides unlimited access control, insensitive to emotions and other behavioral aspects such as exhaustion, abduction, and sexual assault, … etc. Furthermore, the finger knuckle print (FKP) is a universal, one-of-a-kind, and permanent biometric pattern used for very precise personal recognition. Contactless/unconstrained acquisition, robust feature extraction, and fusion strategies have been the subject of recent FKP research [3, 4].
A unimodal biometric system is a system that uses a single biometric trait [5] or an information source for verification or identification purposes [6]. Single-mode systems have steadily improved in terms of accuracy and reliability. However, they often suffer from the issues due to non-universal biometric traits, identity theft, and lack of precision due to noisy data. Additionally, single-mode biometric systems achieve less desired performance in real-world applications. Therefore, a method to solve these problems based on the use of multimodal biometric recognition systems [7]. This system can be defined as a system that combines the result obtained from more than one biometric characteristic for identification purposes. Unlike a unimodal biometric system which can result in non-universality, a multimodal system uses several biometric modalities which can result in a highly accurate and secure biometric identification system [8, 9].
Our experience is based on the transfer learning features of convolutional neural network methods called VGG. VGG's have recently shown remarkable success in feature extraction, image recognition, computer vision. VGG transfer learning is one of the deep learning techniques that have recently been used by many companies, such as Adobe, Apple, Facebook, Baidu, Google, IBM, Microsoft, NEC, Netflix, and NVIDIA.
This work aims at achieving unimodal and multimodal biometric systems based on multi-sample FKP images using the transfer learning technique. Compared with traditional methods, our proposed VGG could extract more distinctive features and achieve satisfying and best recognition performance. In our experiments, we first evaluate each biometric identification system based on a single finger (unimodal system). Also, the results of two or more unimodal systems are fused at the matching score level to create an efficient and robust multimodal identification system.
The rest of the paper is organized as follows: Section (2) describes the proposed multimodal biometric system in which scores are fused at the matching level. Section (3) briefly describes the transfer learning-based feature extraction method and classification. The fusion rules are illustrated in section (4). In section (5), the experimental results, obtained using a PolyU database of 165 persons, are presented and discussed. Finally, the last section (6) includes the conclusion and the intended perspectives.

2. Proposed System

Figure 1 shows the block diagram of a multi-modal biometric recognition system based on the fusion between FKP samples. The region of interest (ROI) [10] is located and cropped from the FKP images in the preprocessing module. The purpose of the feature extraction by VGG 16 and VGG 19 is to represent the feature vector of each ROI image during the enrollment process. At the end, these feature vectors used as a training database used to create a model (matrix) depending on whether each column corresponds to a feature vector. In the second

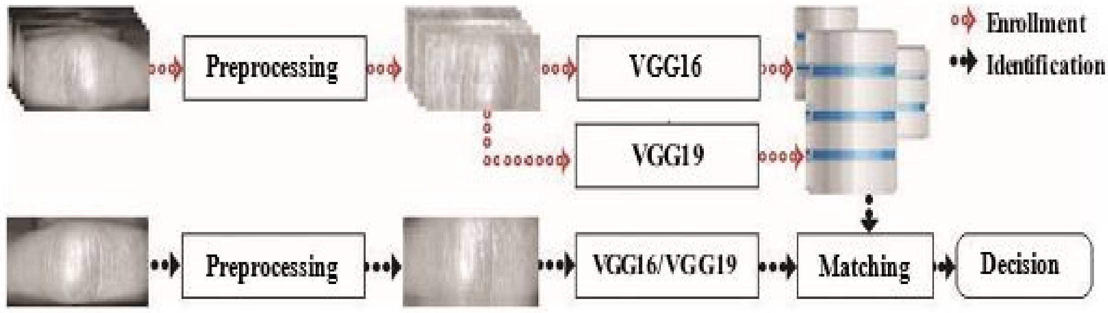

Figure 1: Multimodal Finger Knuckle Print identification system.

phase, devoted to the identification, the same methods used in the enrolment phase is applied to get extract the feature vector from the test image, and then it uses as an input to the matching module in order to find the decision which owns this finger. In the multimodal biometric identification system, the merger process is done at the score level, which is combining the normalized scores of two or more biometric systems. For each user, the system decision is made as follows:

$$Decision = \begin{cases} Accepted, & \text{if} \quad d_0^i \geq \mathcal{T}_{th} \\ Rejected, & \text{if} \quad d_0^i < \mathcal{T}_{th} \end{cases} \tag{1}$$

where d_0^i indicates the probability for the i^{th} person and (T_0) the system security threshold provided by the system designer (depending on the desired security level). This enhanced scheme takes advantage of each biometric modality and can be used to improve the unimodal biometric system.

3. Feature Extraction and Classification

VggNet is a deep convolutional network [11] for object recognition that was created and educated by Oxford's renowned Visual geometry community (Vgg), and which performed exceptionally well on the ImageNet dataset. Convolutional layers were stacked on top of each other at rising depths to create the Vgg network .

VGG is a further enhancement to AlexNet that makes the network deeper. the structure of VGG is shown in Fig. 2. Because the size of the whole convolution kernel is 3×3, the structure of VGG is neat and its topology is simple, the small size of the convolution kernel also brings advantages such as increasing the number. VGG expands the number of CNN layers to more than 10, improving the expressive capacity of the network and facilitating subsequent changes in the structure of the network [12].

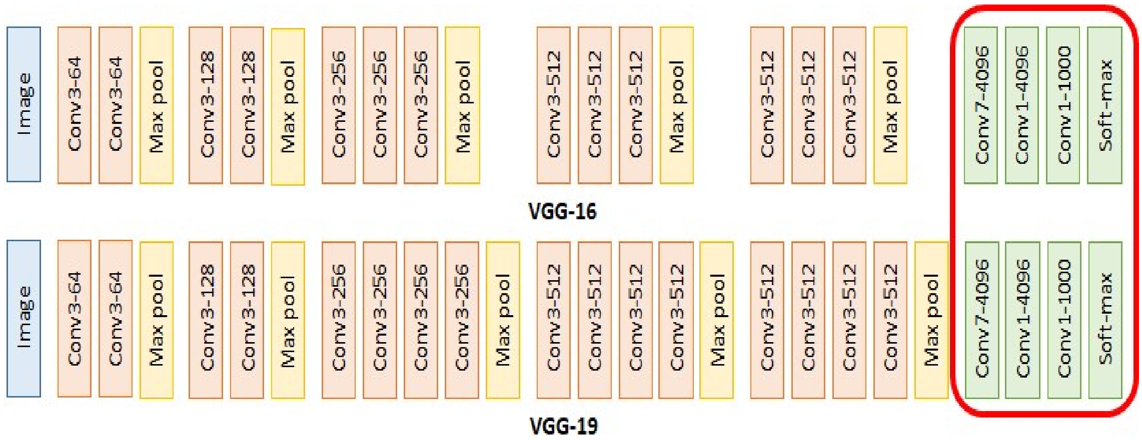

Figure 2: Architecture of Vgg16 and Vgg19.

3.1. VGG16

Unlike AlexNet, VGG16 consists of a replicative structure of convolution, reread, and pooling layers. They increased the number of these network units to design a deeper network. However, Simonyan et all [13] considered a smaller receive window for each convolutional filter compared to AlexNet. With the preservation of the same nonlinear activation unit of AlexNet.

3.2. VGG19

In addition, a deeper VGG19 network is offered for the same task (object detection). VGG19 included some additional convolutional rereaders in the middle of the array compared to VGG16. However, this minimal change in architecture turns into an improvement in accuracy for the object recognition task.

4. Matching, Fusion Scheme and Decision

Matching score is a measure of similarity between the test (input) and train (template) feature vectors. The high match score can be determined by examining the match scores appertaining to all the comparisons and reporting the identity of the template corresponding to the largest similarity score. Recently, several methods have been used in this field, and in our biometric identification system we used three different types (Support Vector Machine (SVM), k-Nearest Neighbor (KNN), and Random Forest (RF)).

4.1. Support Vector Machine (SVM)

SVM is a kind of machine learning algorithm that can be used to solve problems like classification, regression, and detection. A support vector machine is a technique of discrimination, it is a supervised learning method for classification and regression. It consists in separating two or more sets of points by a hyperplane. Depending on circumstances and configuration points. The original idea of SVM is based on using kernel core functions that allow optimal separation of the points of the plan in different categories. The method uses a set of training data. which enables a hyperplane separating the best points. In this paper we use the multi class SVM [14].

4.2. K-Nearest Neighbor (KNN)

K-nearest neighbor is the traditional supervised statistical pattern recognition method which classifies an image by comparing the 'K' value of the training data with test data for finding closeness with the testing image or data. The 'K' values are estimated from the feature extraction carried out during the training process. Euclidean equation principle is employed in KNN classifier for identifying the similarity [15].

4.3. Random Forest (RF)

A random forest is a set of unconditional classifications or regression trees that were constructed using bootstrap samples from training data and random feature selection in tree extrapolation. Forecasting is done by compiling (majority or average vote) the group's forecasts. Two methods for essemble learning a classification tree. The sample subsets creation for a tree is dependent on previous classification results and addition weights are given to the samples that are incorrectly predicted previously [16].

Fusion at the matching score level is the most popular and frequently used method because of its good performance and simplicity. The outputs of the two or more matching modules (LIF, LMF, RIF, RMF) are combined using fusion at the matching-score level.
There are several matching-score fusion rules integrate normalized matching scores of a user to produce the final matching score [17].

4.3.1. Simple Sum Rule

The Simple Sum rule takes the sum of the R matching scores of the $(k)_t h$ user as the final matching score S_k of this user. S_k is calculated as follows:

$$S = 1/N \sum_{i=1}^{N} S_i \tag{2}$$

4.3.2. Product rule

This rule defines the new scores for each matcher, is calculated as follows:

$$S = 1/N \prod_{i=1}^{N} S_i \tag{3}$$

4.3.3. Minimum rule

This rule simply sets a new scores as the minimum score of each matcher's scores, is calculated as follows:

$$S = min(S_i) \tag{4}$$

4.3.4. Maximum rule

This rule simply sets a new scores as the maximum score of each matcher's scores, is calculated as follows:

$$S = max(S_i) \tag{5}$$

The final result of the fusion is a new matching score, which is the basis for the classification decision of the entire system.

4.3.5. Weighted Sum rule

The weighted sum of the R matching scores, which is shown in (6), is considered as the final matching score of the k_{th} user.

$$S = \sum_{i=1}^{N} w_i S_i \tag{6}$$

whereW_i represents the weight of the matching score of the i_{th} biometric trait of the k_{th} user. And

$$w_i = \frac{1/\sum_{i=1}^{N} 1/EER_j}{EER_i} \tag{7}$$

4.3.6. Weighted Product rule

Let W_i stand for the weight of the matching score of the i_{th} biometric trait of the k_{th} user. A Weighted Product rule can determine the final matching score of the k_{th} user using

$$S = \prod_{i=1}^{N} w_i S_i \tag{8}$$

The final result of the fusion is a new matching score, which is the basis for the classification decision of the entire system.

5. Experimental Results and Discussion

5.1. Experimental datasets

To evaluate the performance of the proposed biometric system and choose their appropriate parameters, a database of FKP images is required. Thus, our experiment tests were performed using the FKP Database from the Poly University (The Hong Kong Polytechnic University 2018) [18]. The database has a total of 7920 images from 660 different fingers obtained by 165 persons. This dataset including 125 males and 40 females. Among them, 143 subjects were 20–30 years

TABLE I : Unimodal Identification Test Results Using SVM classifier

Fingers	Open Set		Closed Set	
	VGG 16 Features			
	T_o	EER(%)	ROR(%)	RPR
LIF	0.9320	6×10^{-4}	99.79	02
LMF	0.8550	3.7×10^{-3}	99.79	03
RIF	0.6850	0.1016	99.79	41
RMF	0.8460	8×10^{-3}	99.69	05
	VGG 19 Features			
LIF	0.8640	3.7×10^{-3}	99.39	03
LMF	0.7120	1.36×10^{-2}	99.79	32
RIF	0.6720	0.1010	99.69	69
RMF	0.8250	3.7×10^{-3}	99.89	04

TABLE II : Unimodal Identification Test Results Using KNN classifier

Fingers	Open Set		Closed Set	
	VGG 16 Features			
	T_o	EER(%)	ROR(%)	RPR
LIF	0.090	0.1010	99.39	10
LMF	0.058	0.045	99.19	05
RIF	0.098	0.2020	99.09	32
RMF	0.075	0.1010	99.19	14
	VGG 19 Features			
LIF	0.1487	0.2441	98.78	20
LMF	0.126	0.1010	99.69	85
RIF	0.1457	0.3030	98.48	47
RMF	0.1331	0.2020	99.09	20

TABLE III : Unimodal Identification Test Results Using RF classifier

Fingers	Open Set		Closed Set	
	VGG 16 Features			
	T_o	EER(%)	ROR(%)	RPR
LIF	0.6200	0.3172	97.07	32
LMF	0.6820	0.1133	98.58	14
RIF	0.6370	0.2772	98.18	33
RMF	0.6180	0.3030	97.47	22
	VGG 19 Features			
LIF	0.5650	0.5057	97.27	30
LMF	0.6260	0.2020	98.10	40
RIF	0.5710	0.3030	97.97	43
RMF	0.5350	0.5044	97.97	52

old and the others are 30–50 years old. These images are collected in two separate sessions. The average time interval between the first and the second sessions was about 25 days. The maximum and minimum intervals were 96 and 14 days, respectively. In each session, the subject (person) was asked to provide 12 image samples for each of Left Index Fingers *LIF*, Left Middle Fingers *LMF*, Right Index Fingers *RIF* and Right Middle Fingers *RMF*. . Therefore, 48 image samples from 4 finger types were collected from each person.

To develop a finger knuckle print recognition system, it is necessary to have two databases: a database to perform training (learning) and other database to test and determine their performance. For the vgg technique, it is best to take more comprehensive training data to avoid overfitting. In our set of tests, we divided the database as follows: The odd images of each person are used for the learning phase, the remaining 6 (even) images of each individual were used for the various tests.

5.2. Experimental Setup

In this section, the identification tests results are divided into three parts. In the first part, a series of experiments were carried out to use the Vgg transfer learning features to evaluate the performance of the proposed unimodal biometric system using the different FKP finger knuckle print samples. For this, both identification modes (open-set and closed-set modes) are tested. In the last section, the performance of the multimodal biometric system is evaluated. Our biometric system is implemented using MATLAB 2020a in an experimental platform as a workstation (HP Z8 G4), with a 64-bit Microsoft Windows 10 operating system, equipped with an Intel Xeon Silver 4108 processor, a 96 GB of RAM and a graphic processing unit (GeForce RTX 2080 Ti, GeForce RTX 3090).

5.3. Unimodal biometric System Test Results

The goal of this experiment is to evaluate the system performance when we using information from each modality (each finger). For this, in Open Set identification we found the performance under different modalities (LIF, LMF, RIF, RMF).

Table I, II, III compares the performance of the unimodal system based on VGG feature extraction and different classifier for various fingers. The experimental results indicate that the vgg 16 perform better than the vgg 19 when using all classifier SVM, KNN, and RF. For that, the LIF give the best result compared to all fingers in terms of EER. They give $EER = 6 \times 10^{-4}\%$ in SVM classifier, $4.5 \times 10^{-2}\%$ in KNN classifier respectively. As a result, the SVM classifier is the best compared to all other classifiers.
The tables compare the closed-set identification results. Like the open-set identification biometric system, the closed-set identification system can achieve high accuracy with the vgg method. In this case, the system generates a Rate-One Recognition (ROR) equal to 97.07% up to 99.89% with a Rank of Perfect Recognition (RPR) equal to 02 up to 85 for all fingers and classifier.

5.4. Multimodal Biometric System Test Results

Unimodal systems are Faced several problems, such as the possibility of noise in the biometric modality and its non-universality, Intra-class dissimilarity, and inter-class similarity. all this problem increases the system error (EER) and hence the result of identification.

TABLE IV : MULTIMODAL BIOMETRIC IDENTIFICATION SYSTEM TEST RESULTS

Fusion rules	LIF-LMF				RIF-RMF			
	Open Set		Closed Set		Open Set		Closed Set	
	T_o	EER(%)	ROR(%)	RPR	T_o	EER(%)	ROR(%)	RPR
SUM	**0.712**	**0.00**	**100**	**01**	**0.733**	**0.00**	**100**	**01**
WHT SUM	**0.869**	**0.00**	**100**	**01**	0.9090	8.6×10^{-3}	**100**	**01**
PROD	**0.522**	**0.00**	**100**	**01**	**0.642**	**0.00**	**100**	**01**
WHT PROD	**0.837**	**0.00**	**100**	**01**	0.9950	8.52×10^{-3}	**100**	**01**
MIN	**0.666**	**0.00**	**100**	**01**	**0.828**	**0.00**	**100**	**01**
Max	/	/	**100**	**01**	/	/	**100**	**01**

Fusion rules	LF-RF All Fingers			
	Open Set		Closed Set	
	T_o	EER(%)	ROR(%)	RPR
SUM	**0.718**	**0.00**	**100**	**01**
WHT SUM	**0.845**	**0.00**	**100**	**01**
PROD	**0.174**	**0.00**	**100**	**01**
WHT PROD	**0.800**	**0.00**	**100**	**01**
MIN	**0.606**	**0.00**	**100**	**01**
MAX	/	/	**100**	**01**

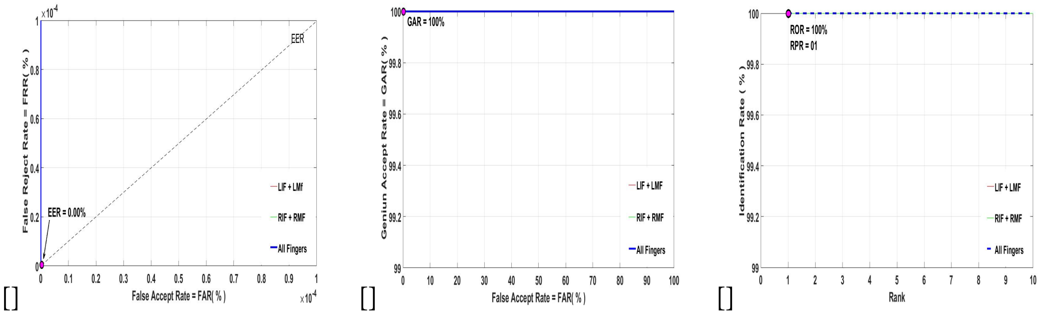

Figure 3: Multimodal biometric identification system test results. (a) ROC curves (FRR against FAR), (b) ROC curves (GAR against FAR) and (c) CMC curves, identification rate against rank.

An excellent biometric identification system requires a very low EER value, which can be achieved by the multimodal system. This system combined several features of each modality at different levels, namely the sensor level, the feature level, the matching score level, and the decision level [19].

The goal of the fusion process is to improve the performance by fusing the information from different modalities. We will try to merge the different scores for different fingers to obtain a multimodal system.

In this case, we merge the different samples of some fingers (LIF and LMF, RIF and RMF) and at the end we realize a system based on the fusion between the two fingers (LIF+LMF), (RIF+RMF), and all fingers. For that, we use the results obtained by VGG 16 transfer learning features and SVM classifier.

Table IV and Fig 3 show the performance of the multimodal identification system using different fusion rules, from the results, we note that the all rules give the perfect result with the LIF+LMF, RIF +RMF, and all fingers in combinations, they gives $EER = 0.00\%$ in Open-Set identification. In Cloused-Set, the system generates a Rate-One Recognition (ROR) equal to 100%. The analysis of the data showed that the results of the multimodal fusion were much better than those of the unimodal biometric systems.
The multimodal system has an $(EER = 0.00\%)$ and an $(ROR = 100\%)$ and an $(RPR = 01)$, thereby obtaining a perfect result. This is ideal precision can be reduced to a large database. The all rules are the best because it gives a perfect result and it is simple to use.

6. Conclusion and Further Work

This paper produces a multimodal identification system based on finger knuckle print using the merge of different samples (LIF, LMF, RIF, and RMF fingers) at the matching score stage. In this case, we implemented the VGG transfer learning method to extract the FKP features. The experimental results illustrate that the combination of finger modalities images outperforms compared with single finger modality. It produces very low EER 0.00% in open-set identification and a high ROR 100% in closed-set identification.
In conclusion, the fusion schemes with multimodal systems gave significantly better performances than their unimodal systems. Our future work will project to use other modalities like (Palmprint, Face, Voice,...etc) with other transfer learning methods (like AlexNET, ResNet, DenseNet, Inception ResNet v2, Inception v3, Inception v4, and Xception).

References

[1] P. Campisi, Security and privacy in biometrics, volume 24, Springer, 2013.
[2] J. Unar, W. C. Seng, A. Abbasi, A review of biometric technology along with trends and prospects, Pattern recognition 47 (2014) 2673–2688.
[3] A. Kumar, C. Ravikanth, Personal authentication using finger knuckle surface, IEEE Transactions on Information Forensics and Security 4 (2009) 98–110.
[4] K. Usha, M. Ezhilarasan, Finger knuckle biometrics–a review, Computers & Electrical Engineering 45 (2015) 249–259.
[5] S. Venkatraman, I. Delpachitra, Biometrics in banking security: a case study, Information Management & Computer Security (2008).
[6] A. Drygajlo, Multimodal biometrics for identity documents and smart cards: European challenge, in: 2007 15th European Signal Processing Conference, IEEE, 2007, pp. 169–173.
[7] M. El-Abed, R. Giot, B. Hemery, C. Rosenberger, A study of users' acceptance and satisfaction of biometric systems, in: 44th Annual 2010 IEEE International Carnahan Conference on Security Technology, IEEE, 2010, pp. 170–178.
[8] M. Mittal, B. Garg, Secure identity using multimodal biometrics, Int. J. Inf. Technol. Knowl. 7 (2014) 20–25.
[9] H. Jaafar, D. A. Ramli, A review of multibiometric system with fusion strategies and

weighting factor, International Journal of Computer Science Engineering (IJCSE) 2 (2013) 158–165.

[10] C. Hegde, P. D. Shenoy, K. Venugopal, L. Patnaik, Fkp biometrics for human authentication using gabor wavelets, in: TENCON 2011-2011 IEEE Region 10 Conference, IEEE, 2011, pp. 1149–1153.

[11] H. Jun, L. Shuai, S. Jinming, L. Yue, W. Jingwei, J. Peng, Facial expression recognition based on vggnet convolutional neural network, in: 2018 Chinese Automation Congress (CAC), IEEE, 2018, pp. 4146–4151.

[12] L. Shao, F. Zhu, X. Li, Transfer learning for visual categorization: A survey, IEEE transactions on neural networks and learning systems 26 (2014) 1019–1034.

[13] K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition, arXiv preprint arXiv:1409.1556 (2014).

[14] C.-C. Chang, C.-J. Lin, Libsvm: a library for support vector machines, ACM transactions on intelligent systems and technology (TIST) 2 (2011) 1–27.

[15] S. Shakya, Analysis of artificial intelligence based image classification techniques, Journal of Innovative Image Processing (JIIP) 2 (2020) 44–54.

[16] F. Ahmad, K. Roy, B. O'Connor, J. Shelton, G. Dozier, I. Dworkin, Fly wing biometrics using modified local binary pattern, svms and random forest, International Journal of Machine Learning and Computing 4 (2014) 279.

[17] D. Samai, K. Bensid, A. Meraoumia, A. Taleb-Ahmed, M. Bedda, 2d and 3d palmprint recognition using deep learning method, in: 2018 3rd International Conference on Pattern Analysis and Intelligent Systems (PAIS), IEEE, 2018, pp. 1–6.

[18] R. Chlaoua, A. Meraoumia, K. E. Aiadi, M. Korichi, Deep learning for finger-knuckle-print identification system based on pcanet and svm classifier, Evolving Systems 10 (2019) 261–272.

[19] A. Jain, K. Nandakumar, A. Ross, Score normalization in multimodal biometric systems, Pattern recognition 38 (2005) 2270–2285.