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PALMPRINT RECOGNITION USING VGG16

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Abstract- Handprint recognition is one of the most interesting and challenging problems in computer vision for pattern recognition. Recent years have seen palm print recognition gain prominence over traditional applications such as forensics and security analysis. The VGG16 was chosen as the central network in this article because it outperforms AlexNet as it replaces large-core filters (11 and 5 in the first and second convolutional layers, respectively) with numerous 3×3 kernel-sized filters. The VGG16 network topology is unusual and reasonably straightforward to change; it can be adjusted to various datasets and is particularly adaptable to other datasets. A total of 13,982 input images are split into 20% for testing and 80% for training, then the images are entered into layers of convolution and max-pooling till the features are extracted and then categorized using the SoftMax function. A MATLAB 2017a version of the method was used to test and implement the method on the Chinese Academy of Sciences-CASIA PalmprintV1 database of 5502 palm prints, the CASIA Multi-Spectral PalmprintV1 database of 7200 palm prints, and the THUPALMLAB database of 1280 palm prints. The classification accuracy ratio of this method is high of 13,982 image and reaches 97.32% in palm print recognition on the database (CASIA palmprintV1, CASIA Multi-Spectral palmprintV1, and THUPALMLAB). As a real-time detection system, the speed is acceptable, and the performance is stable as well. The equal error rate was 0.0268.

Keywords: Convolutional Neural Network (CNN), Palm Print Recognition, VGG16, Security.

1. INTRODUCTION

Passwords and ID cards were the traditional way of identifying people, but they are commonly overlooked or stolen [1]. A biometric authentication system simplicity, trustworthiness, and distinctiveness has made it a popular choice over the past few years [2]. The identification of a person using their behavioral characteristics like speech [3], voice, signature, keystroke dynamics, gaits etc., or biological features including fingerprints, faces, veins, iris, palm prints, skin texture, etc. is becoming a trend where multi-biological features are merged rather than focusing on single-mode features in biometric authentication technology. The palm print is a modern and excellent way to ensure the security and confidentiality of the information and financial transactions [4].

This technology entered the field of computers and gates in airports and companies, and its use by the security services at airports because its use is safe and not subject to tampering, as the palm contains major lines and minor lines (wrinkles) and skin edges [5]. The palm contains more information than a fingerprint, including indents, textures, and marks that can be used to compare palms [6]. Palm print refers to the image taken from the palm area. It can be either an online image (i.e., captured by a charge-coupled device (CCD) or scanner) or an offline image where the image is captured in ink and paper [7]. An individual's palm prints contain a multitude of details, such as a single dot, fine dot, lines, textures, wrinkles, and edges, which can aid in identifying the individual, refer to Figure 1. Figure 2 shows a pattern matching based on features [1].

This paper used several databases, the first being CASIA palmprintV1 with 5502 images taken from 312 subjects. Subjects are asked to collect their left and right palms. A self-developed palmprint recognition device scans all the images as 8-bit grey-level JPEGs. Figure 3 shows a palm print from CASIA PalmprintV1 [8]. A second database consists of 7,200 palm prints taken by self-designed multispectral imaging devices from 100 different people. JPEGs with 8-bit grey levels are used in all palm images. Two sessions of palm images are captured for each hand. There are three samples in each session, separated by over a month [9]. Figure 4 shows a palm print from CASIA-Multispectral-PalmprintV1. An additional palm print database called THUPALMLAB provides 1,280 palm print images taken with a Hisign palm print scanner from 80 individuals (two palms with eight impressions each). The images are all 2040×2040 pixels and 500 ppi resolution [10]. Figure 5 shows a palm print from THUPALMLAB. Basic neural networks are information processing systems that are aimed at learning, generalizing, and recalling.

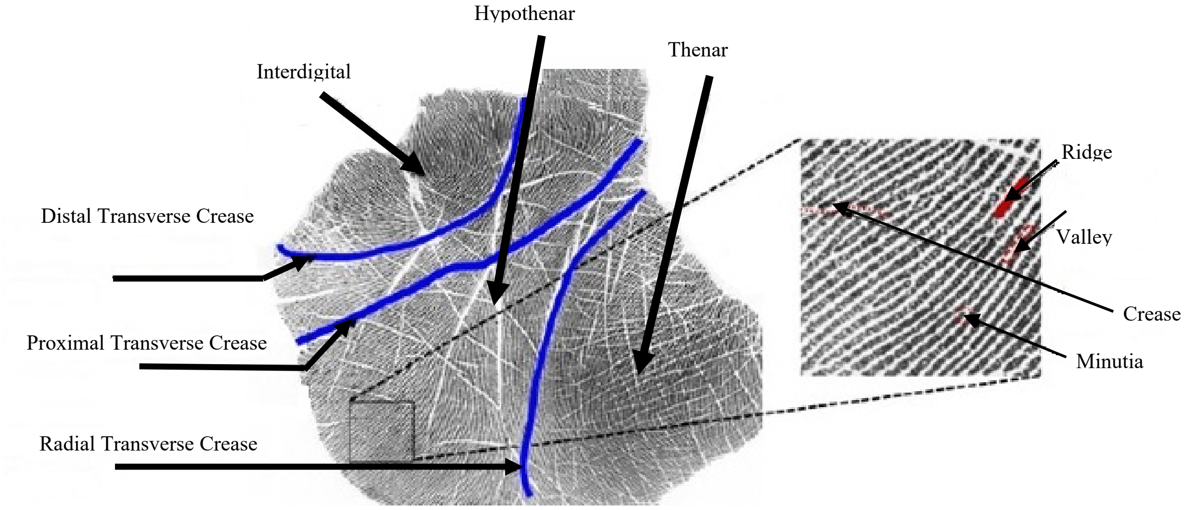

Figure 1. Details of palmprint [7]

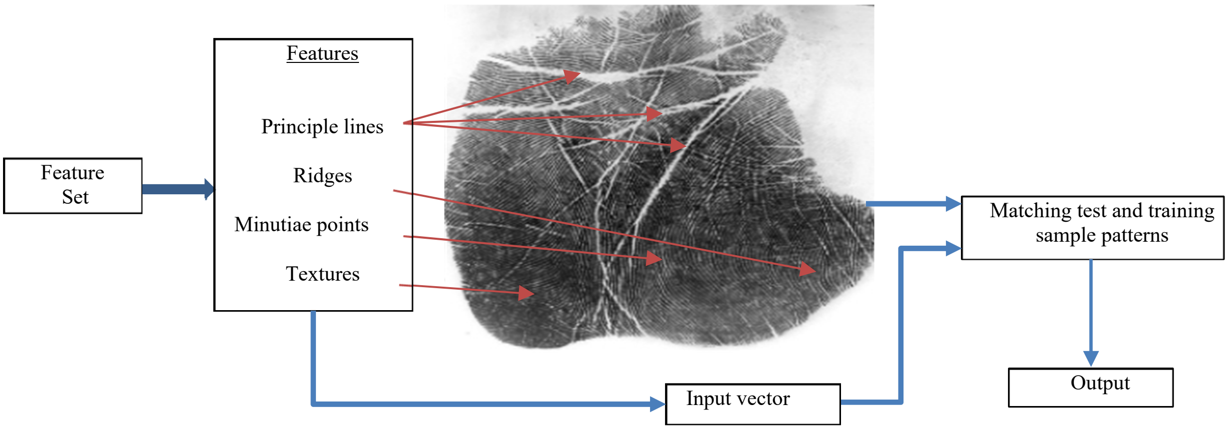

Figure 2. Pattern matching based on features [1]

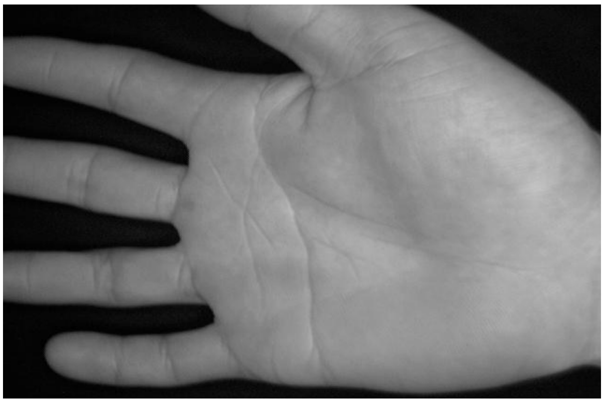

Figure 3. Palm print from CASIA palmprintV1 [8]

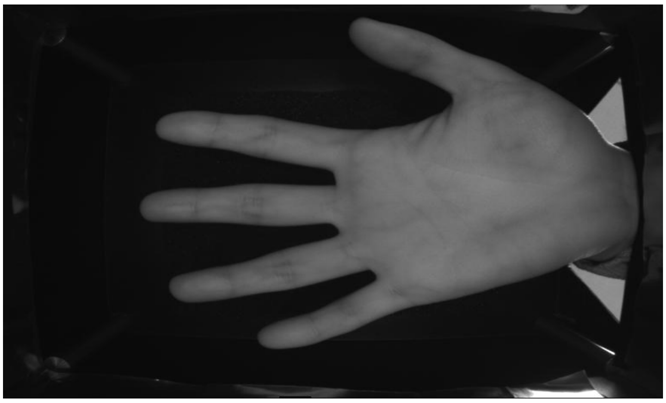

Figure 4. Palm print from CASIA-Multispectral-PalmprintV1 [9]

Figure 5. Palm print THUPALMLAB [10]

Artificial neural networks (ANN) operate based on artificial nerve cells, the smallest and simplest units of information processing [11]. A deep convolutional neural network (CNN) with 16 layers, called the VGG16 DCNN, will be used in this paper for palm print recognition. The VGG16 is an object detection and classification algorithm capable of classifying 1,000 images from 1,000 different categories with an accuracy of 92.7%. It is one of the popular algorithms for classifying images and it is easy to use with transfer learning [5]. Additionally, the ImageNet database was used to train a convolutional neural network [7]. The VGG16 proved to be a milestone in humanity's quest to make computers "see" the world. Much effort has been put into improving this ability under the Computer Vision (CV) system for several years. The VGG16 is one of the important innovations that paved the way for many of the ensuing innovations in this field [12]. Figure 6 shows ImageNet results of VGG16 Vs others.

The paper is organized as follows: within the next part, the related works are presented. Section 3 introduces the structure of the palmprint system. Section 4 discusses the outcomes of the suggested new algorithm. Section 5 then outlines the findings.

2. RELATED WORKS

Over the last decade, several papers have been published about palmprint recognition. Utilizing two-dimensional discrete wavelet transform (2D-DWT), Imtiaz, H., and Fattah, S. A, developed a multi-resolution palmprint recognition algorithm that leverages spatial differences in the palmprint image. The image is divided into several small areas, each of these units is local. The palm print recognition system is based on the extraction of the dominant wave. The process of identifying dominant features and performing a thresholding operation on them does not only greatly reduce feature dimensions but also captures details that are present within the handprint image. Compared to some modern patterns, this pattern is more accurate and computationally complex, where they used different databases for palm printing, in which the accuracy reaches higher than 99% [2]. D. Hong, et al. developed a method using a multispectral palm print rather than a natural light comfort fingerprint. The method was used for obtaining a high recognition rate with more discriminatory data and a multispectral handprint recognition method based on hierarchical recognition. As an approximate feature, they extract Block Dominant Orientation Code (BDOC) and BHOG as a good feature. On the basis of these two types of features, they proposed a hierarchical recognition approach. They blended the various elements to achieve excellent accuracy.

The testing findings revealed that the utilized approach has a very good identification accuracy, and they used the PolyU database with handprints in natural light and recognition accuracy (EER 0.0074 %) [13]. Q. Sun, et al., suggested a technique for extracting handprint characteristics based on a deep convolutional neural network (CNN) that integrates low/medium/high-level features organically and performs well in image, video, and audio processing. To extract palmprint information and properly assess convolutional characteristics, they utilized CNN-F architecture. They employed PolyU's public palmprint database for testing findings, which show that the palmprint characteristics of CNN-F achieve 100% certified perfect recognition rate, validation of correctness, and an EER rate of 0.25%, indicating the reliability and accuracy of the CNN palm print features used [14].

D. Zhong, et al., suggested a new approach for end-to-end palmprint identification based on the Siamese network. Two parameter-sharing VGG-16 networks are utilized in this technique to excerpt a pair of convolutional features from two handprint images, in which the top network determines whether two input palm prints are similar. On the PolyU data set, this approach worked well, yielding a high discrimination result with an equal error rate (EER) of 0.2819%. They did, however, employ a manual palmprint dataset named XJTU from the working environment. The method's EER rate at XJTU is 4.559%, highlighting the application of palmprints in the personal identity system [15] A. Genovese, et al. suggested a touch-free palm print recognition system for high-accuracy identification of persons, based on two novel and latest CNN. The approach employs a novel filter application idea based on Gabor and PCA in CNN, in which the architecture of CNNs is trained using an unsupervised procedure and customized to extract extremely diverse characteristics of fingerprint samples utilizing databases collected using various hardware. In all databases they analyzed, they achieved >95% classification accuracy [12]. Table 1 summarize the palmprint-related works.

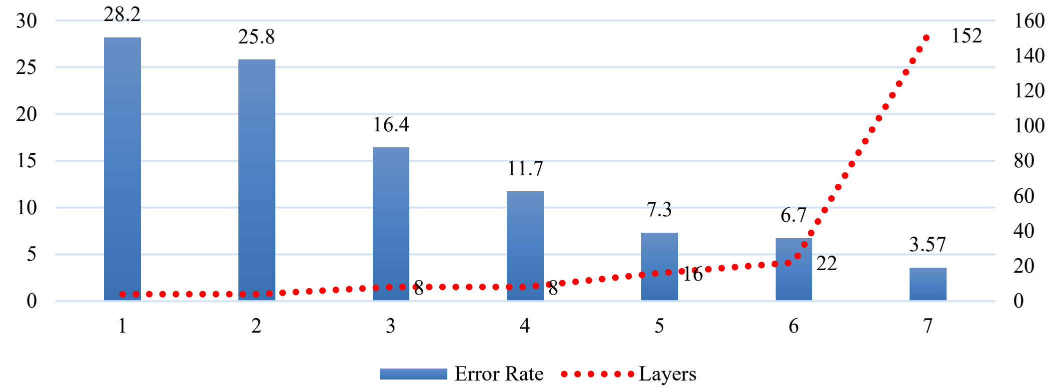

Figure 6. ImageNet results of VGG16 Vs others [12]

Table 1. Summary of the related works

Ref.	Dataset	Methodology
TENGFEI WU, et al., 2021	PolyU, Multi-spectral, IITD, and Tongji	Using Deep Hashing Network (DHN) that represented as a binary bit string
Xuefeng Du, et al., 2020	By mobile phones	Using Deep Hashing Network (DHN) and Maximum Mean Discrepancy (MMD)
Tarawneh, et al., 2018	MOHI, COEP	Applying pre-trained CNNs for feature extraction, followed by (SVM) for classification.
Leng, et. al., 2017	Multimedia University's contactless database (202 palms ×10) = 2020	Using the two-dimensional discrete cosine transform to extract palmprint characteristics (2DDCT).
Fei, Xu, et. al., 2016	PolyU, and ITTD	Double-Orientation Code
Jabid, et al., 2010	CK and JAFFE	LDP texture descriptor
Zuo, et al., 2010	PolyU, and CASIA	As an extension of the PalmCode approach, the competitive-Code method included several Gabor filters.
Wang, et al., 2006	UST	Local Binary Patterns (LBP)
Lin, et al., 2005	4800 images gathered from 160 subjects provide a unique dataset.	The main line of the palmprint is extracted using hierarchical decomposition methods.
Kong, Zhang, 2004	PolyU	The Gabor filter was employed by the robust texture-based features technique to extract orientation information.
Connie, Teoh, 2003	Customized database (100 people ×6 images) = 600 images	Image dimension reduction, as in principal component analysis approaches (PCA)
D. Zhang, et al., 2003	PolyU	An individual Gabor filter was used to encode each pixel in PalmCode method

3. SYSTEM STRUCTURE

Traditional feature extraction methods are based on dimensionality reduction or on minimal feature extraction of the feature set. The advantages of these methods include reducing computing time, but they reduce performance, which is a key factor in biometric systems. With contactless-based systems where there are no restrictions on the capturing stage, it is impossible to have all features appear for each captured image. For instance, because for some reasons such as temperature, light, dust, etc., many features extracted by usual methods may mask and impair image quality, resulting in some feature loss, and in order to increase performance and false rejection rates decreases.

However, by using a Neural Network, which trains all features, there is a greater chance of them appearing in other images, even if not all of them appear in a single capturing image. To address this issue, we propose a palm print depends on the biological system, which uses a large-scale image dataset for testing and training, depending on a pre-trained network named VGG16. Figure 7 shows the proposed system scheme. In this system, preliminary processing is used on the data to achieve better results and then the VGG16 algorithm is used to identify palm prints. Algorithm 1 explains the palm print recognition process using VGG 16 for features extraction, and classification.

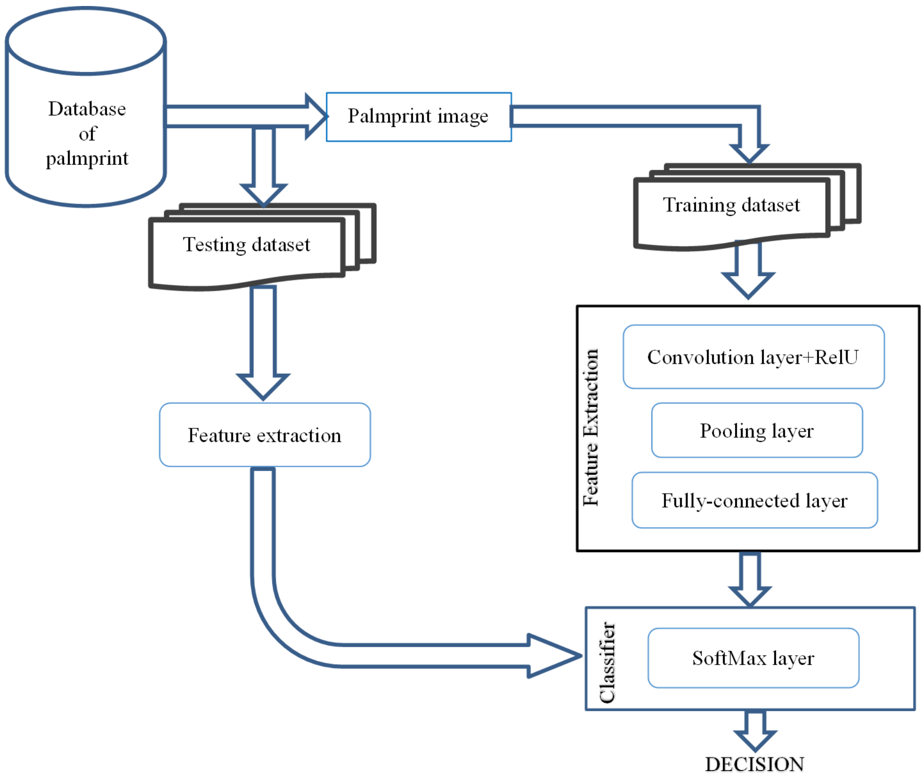

Figure 7. The proposed system diagram

Algorithm 1. Implementation of the major steps for the proposed VGG16 Palm print recognition model

Required: Database images $Img = \{I_1, I_2, I_{3,...}, I_n\}$ a label for palm print images must not similar to the other person and $I \notin \grave{I}$. Training step: First, the weights selected randomly Then, enter [input, correct output] into the convolution layer as the "input". Compute the output error. Calculate the weight updates according to sgdm. Finish training when meeting acceptable performance. Testing step: Extract features from TR. Use the trained classifier Train to predict the label for TR. Get the known labels for TR. Display the accuracy. Evaluation of proposed model by using (Accuracy). End algorithm

The VGG16 is a convolutional neural network (CNN) widened by Simonyan, and Zisermon based on ILSVRC 2014, so far, it is one of the best vision model designs. In VGG16, convolution layers are obtained from a 3×3 step filter but excessive padding and layering are always used from the same 2×2 filter [16, 17]. Figure 8 shows the VGG16 base [18]. It constantly layered torsion and pool extremes passim the entire architecture [19]. A SoftMax output is followed by two FC (fully connected layers) [20]. This network is quite vast, with around 138 million variables. Figure 9 shows the architecture of VGG16 [21].

The size of the input images for the algorithm is 224×224, and the image is converted from grey to color. This method is much more accurate for recognizing palm prints because it uses the VGG16 architecture, which uses RGB and wraps three layers instead of one, so it detects edges better. Because VGG16 detects edges with high accuracy, it is best for recognizing palm prints. The images are separated into 80% for training, 10% for testing, and 10% for validation, then scale them to fit the 16-layer network architecture (VGG-16), where the (13) convolutional layers are 3×3 stacked, and the layers of maximum pooling are 2×2. The Relu activation occurs between these layers. Most of the network parameters are contained in three fully connected layers. Finally, the SoftMax function (the activation function is an integral part of the neural network) [17].

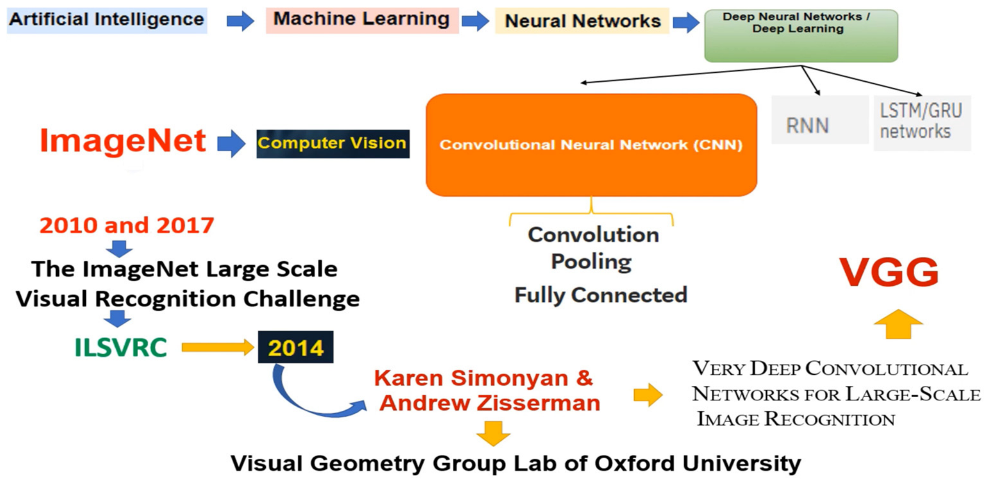

Figure 8. The VGG 16 base [18]

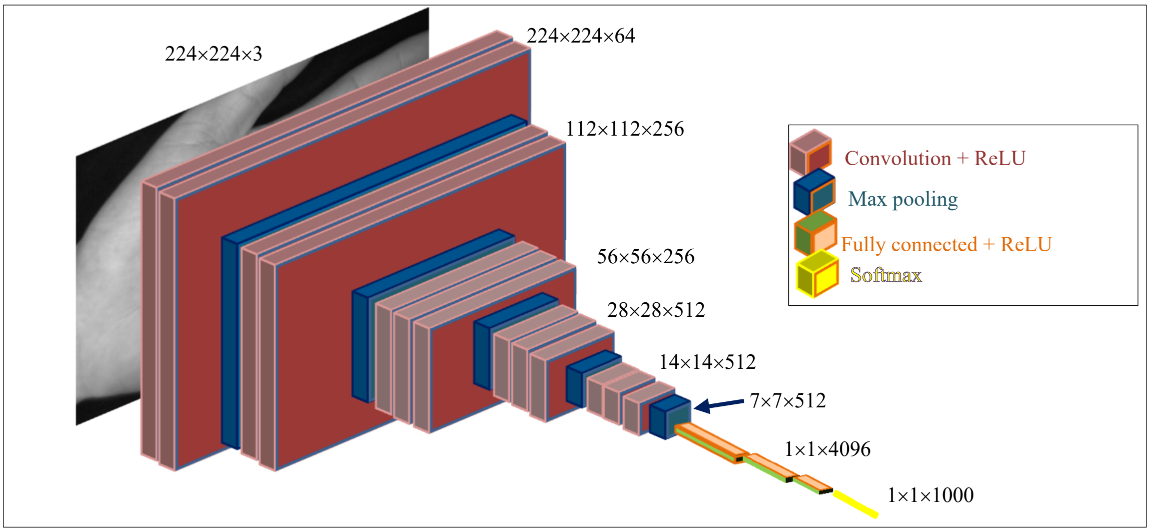

Figure 9. The architecture of VGG16

Table 2 shows the different architecture of VGG [22]. Activation functions give neural networks their nonlinearity, without them, neural networks would be simple linear regression models that produce probabilities based on class assignment. Table 3 shows the architecture of VGG16. The activation function's Equation for the SoftMax is as follows [21]:

$$\text{Softmax}\ (\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_i}} \tag{1}$$

where,

$\vec{z}$: The input is shaped vector to the SoftMax function is made up of (z_0, z_1, z_2, z_3, ... z_k).

z_i: All values of zi are can take any real value and are elements of the input vector into a SoftMax function, negative, zero, or positive. It is not a valid probability distribution, for example, a neural network can have a vector-like (-0.62, 2.53), and that's why SoftMax will be necessary.

e^{z_i}: When applying the standard exponential function to the elements in the input vector. This gives a value higher than 0 means a positive value, which would be too large if the input was large, and too small if the input was negative. In spite of, is still unstable in the range (0, 1) required for probability.

$\sum_{j=1}^{K} e^{z_i}$: The symbol at the bottom of the formula is the normalization symbol. This makes all function output values sum to 1 and all of them are in the range (0, 1), which makes the distribution a very good probability.

K: The number of categories in the multi categories system.

Table 2: Different configurations of VGG [22]

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
Input (224×224 RGB image)					
Conv3-64	Conv3-64 LRN	Conv3-64 Conv3-64	Conv3-64 Conv3-64	Conv3-64 Conv3-64	Conv3-64 Conv3-64
maxpool					
Conv3-128	Conv3-128	Conv3-128 Conv3-128	Conv3-128 Conv3-128	Conv3-128 Conv3-128	Conv3-128 Conv3-128
maxpool					
Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256 Conv1-256	Conv3-256 Conv3-256 Conv3-256	Conv3-256 Conv3-256 Conv3-256 Conv3-256
maxpool					
Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv1-512	Conv3-512 Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512 Conv3-512
maxpool					
Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv1-512	Conv3-512 Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512 Conv3-512
maxpool					
FC-4096					
FC-4096					
FC-1000					
Soft-max					

Table 3. Architecture of the VGG-16 (layer …)

Layer	Patch size	Input size
conv×2	3×3/1	3×224×224
Pool	2×2	64×224×224
conv×2	3×3/1	64×112×112
Pool	2×2	128×112×112
conv×3	3×3/1	128×56×56
Pool	2×2	256×56×56
conv×3	3×3/1	256×28×28
Pool	2×2	512×28×28
conv×3	3×3/1	512×14×14
Pool	2×2	512×14×14
FC	25088×4096	25088
FC	4096×4096	4096

4. THE RESULTS ANALYSIS

In this section, three different databases which are CASIA PalmprintV1, CASIA-Multispectral-PalmprintV1, and THUPALMLAB used in this work. Two of them are contactless, are used to pre-process high-scale images from the dataset for palm print extraction features. A VGG16 neural network is used, to train it with the above datasets. This method is used because it does not require a pre-processing despite using different databases and it was captured with different palm devices. This method has achieved very satisfactory and excellent results. VGG16 uses a filter size of 3×3 per layer. Below is an example of one of these filters:

$$\begin{pmatrix} 0.1662 & 0.2120 & -0.0059 \\ 0.1992 & -0.0259 & -0.0985 \\ -0.0112 & -0.1021 & 0.0273 \end{pmatrix}$$

The convolution process reduces the image dimensions, thus facilitating the process of extracting features, reducing program execution time, speed of work, and improving accuracy. These qualities are required in most applications now and in the future. Figure 10 shows the process of convolution.

The number of filters varies from layer to layer, starting at 64 and then doubling to 512 in the last feature extraction layer. These filters work to wrap the images and reveal the edges. Figure 11 is an example illustrating the processes and changes that occur to the image as it passes through some layers of VGG16.

The proposed system applied to three cases in terms of test images number and the number of training images for an individual. Table 4 shows the results of the proposed system.

- Case 1: using a database of several people in the same class and entering it into the algorithm using epoch=1, the accuracy rate is 80.38% as shown in Figure 12.
- Case 2: making each person an isolated class, the accuracy rate rises to 81.92% with the use of epoch=1 as shown in Figure 13.
- Case 3: making *epoch* = 2, and the accuracy rate rises to 97.32% as shown in Figure 14.

Table 4. The implementation results using different cases

Cases	No. of Epochs	Iteration	No. of Classes	Accuracy rate	EER	Validation Accuracy
Case 1	1	2750	312	80.38%	0.1962	80.01 %
Case 2	1	2693	410	81.92%	0.1808	81.71%
Case 3	2	5386	410	97.32%	0.0268	97.11%

Despite the use of an unbalanced database consisting of images captured with different devices, the performance of the VGG16 was very excellent using an epoch, it reached 80%, and the accuracy increases significantly when increasing epoch's number. Table 5 illustrates the comparison of the current system results with another system. However, the current system is widely used the dataset is too large and some are contactless and difficult to fake.

5. CONCLUSIONS

In this paper, many experiments were performed on the VGG16 algorithm using the imbalance database and a large number of classes, where the number of classes increases and the accuracy rate increases. They were learned using a new, unsupervised technique that does not need class labels, allowing them to use palmprint images that are not linked to the identities of matched individuals. In this research, we extracted very distinctive features from the palm print, which are different databases, and they were combined and used as one base, despite the circumstances in which the images of these rules were taken, and they were captured by different devices and not using pre-processing. In all instances, VGG16 demonstrated greater accuracy than other approaches in the literature in several non-touch palm printing datasets.

Furthermore, VGG16 showed more consistent accuracy results on the heterogeneous. Comparing databases with local texture descriptor techniques, which may underperform in databases for which they were not built. It obtained classification accuracy of more than 97 % in all databases investigated, indicating the viability of employing the VGG16 approach in future datasets recorded using alternative apparatus and acquisition processes. It provided many advantages over previous modern networks. I would like to end this conclusion with this "The contribution of VGG16 to the field of computer vision can be discussed, not disputed".

REFERENCES

[1] Z. Dexing, X. Du, K. Zhong, "Decade Progress of Palmprint Recognition: A Brief Survey", Neurocomputing Vol. 328, pp. 16-28, February 2019.

[2] I. Hafiz, S.A. Fattah, "A Wavelet-Based Dominant Feature Extraction Algorithm for Palm-Print Recognition", Digital Signal Processing, Issue 23, No. 1, pp. 244-258, 2013.

[3] Y. Ouajji, A Mnaoui, H. Najoua, "Intelligent Communication System Based on Automatic Speech Recognition-Compiling Corpus of Phraseology", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 49, Vol. 13, No. 4, pp. 110-114, December 2021.

[4] A.S. Ungureanu, et al., "Toward Unconstrained Palmprint Recognition on Consumer Devices: A Literature Review", IEEE Access 8, pp. 86130-86148, 2020.

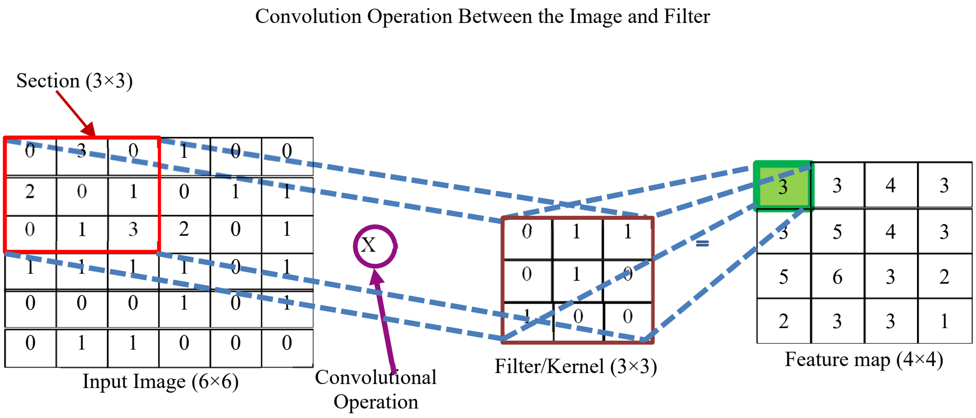

Figure 10. The convolution processes

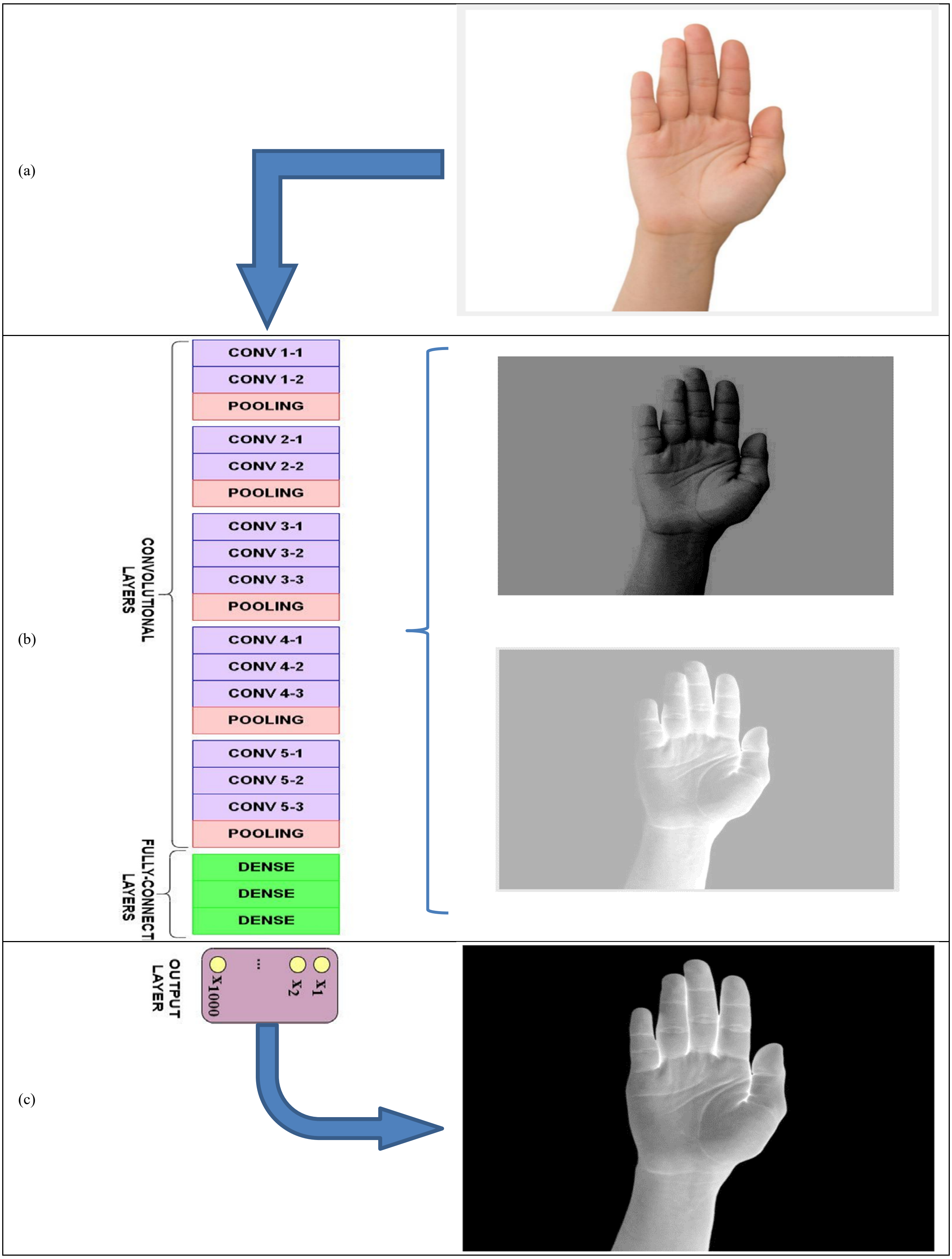

Figure 11. Example of selected convolution image passing through VGG16 layers, (a) Input image, (b) A palmprint result extracted from the VGG16 convolutional network. A small image is the result created through convolution with one of 64 first-level filters that emphasize edges, curves, bright vs dark regions, and shadows among various simple properties, (c) Output image

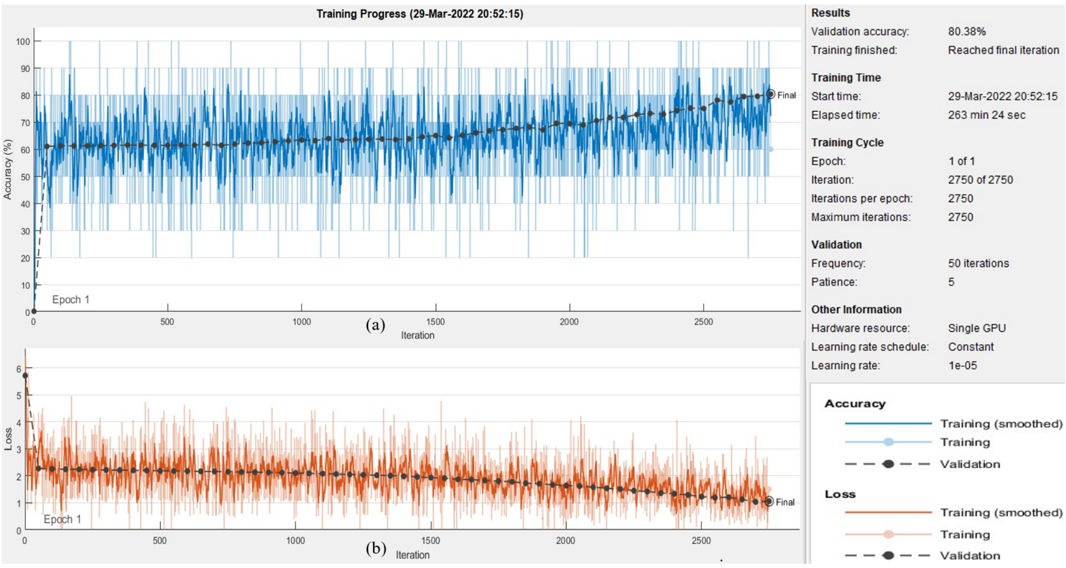

Figure 12. Training over epoch for same images dataset, (a) accuracy rate, (b) loss rate, (epochs=1)

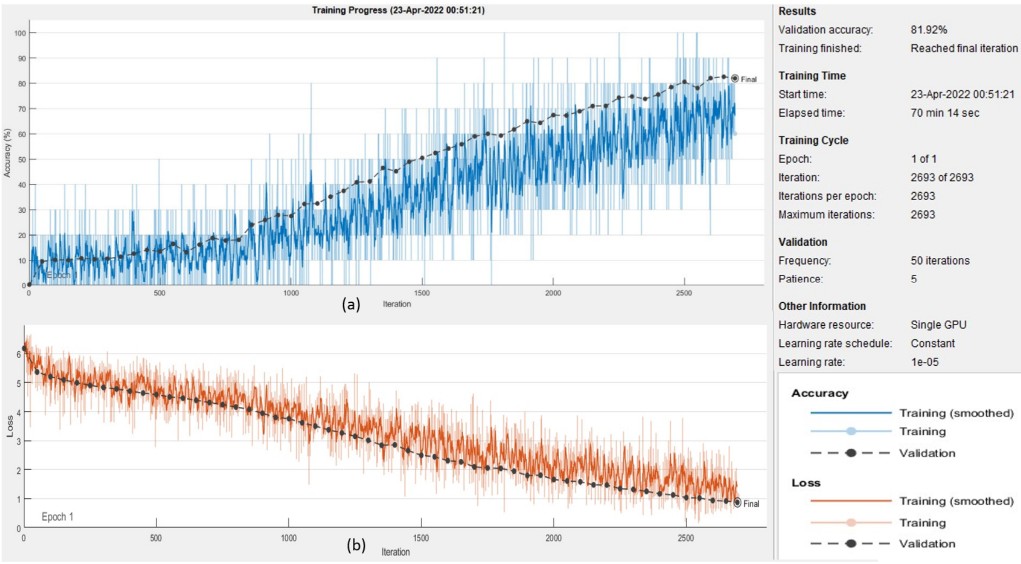

Figure 13. Training over epoch for isolated images dataset, (a) accuracy rate, (b) loss rate, (epochs=1)

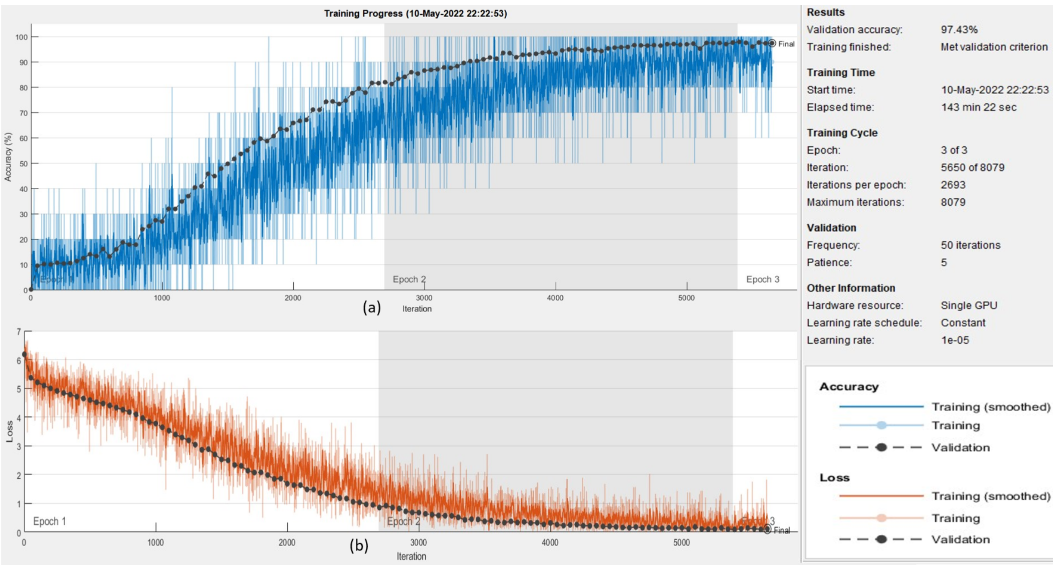

Figure 14. Training over epoch for isolated images dataset, (a) accuracy rate, (b) loss rate, epochs=2)

Table 5. Comparison of the proposed method to the findings of another research

Reference	Dataset	Subject size	Image Size	Acquisition Type	Performance
(Tarawneh, et al., 2018)	MOHI, and COEP	200	3000	Low-quality (smartphone camera) High-quality	*ACC*=95.5%
(Zuo et al., 2010)	PolyU, and CASIA	386 301	7720 5239	Scanner palmprint Scanner palmprint	*EER* = 0.041, 0.48
(A. Ebrahim, et al., 2021)	Tongji large-scale contactless DB	600	12000	Contactless	*ACC*=96.17% *EER*=0.0383
ITTD (Xu, et al., 2018)	PolyUand ITTD	386 460	7720 2300	Scanner palmprint Contactless	*EER*=0.0334
(D.S. Huang, et al., 2008)	PolyU (DB1=100, DB2=386)	100 386	2000 7720	Scanner palmprint	*EER* = 0.49, 0.565
Proposed system	3CASIA and CASIA Multi-Spectral and THUPALMLAB	312 100 160	5502 7200 1280	CCD camera and Contactless (mobile camera) and Scanner palmprint	*ACC*=97.32% *EER*=0.0268

[5] S. Zhao, B. Zhang, "Deep Discriminative Representation for Generic Palmprint Recognition", Pattern Recognition, Issue 98, pp. 107071-107081, 2020.
[6] T. Vijayakumar, "Synthesis of Palm Print in Feature Fusion Techniques for Multimodal Biometric Recognition System Online Signature", Journal of Innovative Image Processing (JIIP), Issue 3, No. 02, pp. 131-143, 2021.
[7] L. Fei, et al., "Double-Orientation Code and Nonlinear Matching Scheme for Palmprint Recognition", Pattern Recognition, Vol. 49, pp. 89-101, 2016.
[8] Z. Sun, et al., "Ordinal Palmprint Representation for Personal Identification", The IEEE International Conference on Computer Vision and Pattern Recognition, Vol. 1, pp. 279-284, Orlando, USA, 2005.
[9] Y. Hao, et al., "Multi-Spectral Palm Image Fusion for Accurate Contact-Free Palmprint Recognition", The IEEE International Conference on Image Processing, pp. 281-284, USA, 2008.
[10] J. Dai, J. Feng, J. Zhou, "Robust and Efficient Ridge-Based Palmprint Matching", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 34, No. 8, pp. 1618-1632, 2012.
[11] A. Genovese, et al., "Gabor-PCA Convolutional Networks for Touchless Palmprint Recognition", The IEEE Transactions on Information Forensics and Security, Vol. 14, No. 12, pp. 3160-3174, 2019.
[12] M. Zile, "Improved Control of Transformer Centers Using Artificial Neural Networks", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 40, Vol. 11, No. 3, pp. 28-33, September 2019.
[13] D. Hong, et al., "A Novel Hierarchical Approach for Multispectral Palmprint Recognition", Neurocomputing, Issue 151, pp. 511-521, 2015.
[14] Q. Sun, et al., "Palmprint Recognition with Deep Convolutional Features", Chinese Conference on Image and Graphics Technologies, Springer, pp. 12-19, Singapore, June 2017.
[15] D. Zhong, Y. Yang, X. Du, "Palmprint Recognition Using Siamese Network", Chinese Conference on Biometric Recognition, Springer, pp. 48-55, Cham, Switzerland, August 2018.
[16] D. Zhang, et al., "Palmprint Recognition Using 3-D Information", IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), Issue 39, Vol. 5, pp. 505-519, August 2018.
[17] K. Simonyan, A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition", arXiv Preprint arXiv, pp. 1409-1556, 2014.
[18] Y. Luo, et al., "Local Line Directional Pattern for Palmprint Recognition", Pattern Recognition, Vol. 50, pp. 26-44, 2016.
[19] A. Kong, et al., "A Survey of Palmprint Recognition", Pattern Recognition, Iss. 42, Vol. 7, pp. 1408-1418, 2009.
[20] J. Dai, J. Zhou, "Multi Feature-Based High-Resolution Palmprint Recognition", The IEEE Transactions on Pattern Analysis and Machine Intelligence, Issue 33, Vol. 5, pp. 945-957, 2010.
[21] M. Loukadakis, J. Cano, et al., "Accelerating Deep Neural Networks on Low-Power Heterogeneous Architectures", The 11th International Workshop on Programmability and Architectures for Heterogeneous Multicores (MULTIPROG), pp. 1-15, Manchester, UK, January 2018.

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