

A Contactless Palmprint Biometric System Based on CNN

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Abstract: Personal recognition systems have emerged as highly important in the information society. Biometric systems are widely used because its reliability in distinguishing between the subjects. Contactless biometric systems are more important because of their advantages, especially, during the pandemic of COVID19 as they can be used to avoid the spread of such viruses. Convolutional neural networks (ConvNet) have also gained a great success in large-scale image. In this study, we try to produce a contactless biometric system based on palmprint and use of Tungji large-scale contactless dataset to implement the system. This paper, divided into five sections, starts with the general introduction; a literature review of related work in the second section; the methodologies and dataset description the third section; the results and implementation steps in the fourth section; and finally, the conclusion and suggestions in the last section.

Keywords: Palmprint, biometric, contactless, touchless, large-scale dataset, convolutional neural networks (ConvNet).

1. Introduction

Personal authentication systems have attracted the attention of many scholars as it proves to be crucial and highly wanted techniques in wide fields of applications: security, attendance, CCTV, and forensics systems are most important examples (Alrahawe et al., 2021; Kumar et al., 2003). In this field, biometric authentication systems are raising a vital position due to its accuracy, capability and reliability. In addition, contactless biometric systems have become highly demanded techniques (Lu et al., 2012), especially after the pandemic of COVID19. Unlike touch-ness systems, touch-fewer systems are considered to be able to prevent the spread of such viruses, which would help the insurance the safety of society. In addition, convolutional neural networks (ConvNet) have gained a great success in large-scale image (Arge & Mage, 2015; Krizhevsky et al., 2012; Sermanet et al., 2014; Simonyan & Zisserman, 2014; Zeiler & Fergus, 2013). Possibility of high performance computing systems serve a large-scale image classification systems with high dimension of features (Arge & Mage, 2015; Perronnin et al., 2010). However, building a large enough dataset is a crucial issue. Unlike traditional biometric systems which try to reduce the dimensionality of the biometric image, the current work uses convolutional neural networks (ConvNet) to propose a contactless recognition biometric system based on palmprint. Using a large-scale palmveins dataset provided from Tongji University (L. Zhang et al., 2018), we preprocesses the dataset in two ways to build two separated datasets using an adaptive threshold of MEAN, and GAUSSIAN. Then separately, builds a neural network model: training, validating and testing processes. We evaluate the system using an important measures, by calculating the TPR, TNR, FPR, FNR, EER, Genuine/Imposter distribution, and Accuracy. We builds a high accuracy recognition system in rate of 96.89% for the MEAN thresholded dataset, and 96.17% for the GAUSSIAN thresholded dataset. After this introduction, the rest of this paper is organized as: the second section concerns with the literature review of related work; methodologies and dataset description derives in the third section; the fourth section discusses the results and implementation steps; finally, the last section concludes the work and provides some suggestions.

2. Review Of Related Studies

Literature reviews concerning Palmprint techniques and methodologies shows that there are three main categories and each category includes sub-categories. These three categories are texture-based coding, line-like feature extracting, and sub-space feature learning (Genovese & Piuri, 2019). Summarized in table (1), they are discussed as follows:

In the Texture-based coding : Approaches in coding-based, specific filters applied on the image, quantizing the magnitudes or phases of the responses to these filters, and then the result have to be encoded to compute the

biometric template. For comparing templates, Hamming distance can be used as a global matcher (Leng et al., 2017). Palmprint coding approach, a robust texture-based features method which uses a Gabor filter to extract the orientation information, then, encodes the response (Leng et al., 2017).

Single Gabor filter applied on an image to encode every pixel in the image, as presented in the PalmCode method (D. Zhang et al., 2003). Later, with different orientations, multiple Gabor filters used as a development to the PalmCode, which enables to determine the palmprint principal lines orientations, as proposed in Competitive-Code method (Zuo et al., 2010), Robust-Line-Orientation Code method (Jia et al., 2008), and Double-Orientation Code (Fei, Xu, et al., 2016). Texture features extracted by applying 2-D Gabor filters from low-resolution images is used to produce an accurate palmprint recognition system (D. Zhang et al., 2003). Another idea proposed is the extraction of biometric template based on multiple orientations in every local region of the image. Encoding the responses of all Gabor filters for every pixel in image, described in Binary Orientation CoOccurrence Vector method (Guo et al., 2009). A Similar to this proposal with a slight difference is Neighboring Direction Indicator (NDI) (Fei, Zhang, et al., 2016). It is different with regard to the relations of the neighboring region orientations; otherwise, it is just the same.

An integration between NDI and Competitive Code methods is the Robust Competitive Code method (Xu et al., 2018), where the most relevant response for each pixel is encoded along with the weighted responses for the neighboring orientations.

Line-like feature extracting : Local-Texture based approaches, considered as an image descriptors, basically encode an intensity values for image pixels, generate the histogram for each local region in the image, obtaining a single-dimensional feature vector by concatenating histograms. This vector represents a corresponding biometric template, which enables the chance for any distance measures to be used for comparing templates (S. A. Orjuela Vargas et al., 2013). Even though it designed for general purposes, Local-Texture descriptors can be used for palmprint recognition. These descriptors are widely used such as Scale-Invariant Feature Transform (SIFT) (Leng et al., 2017), (Wu et al., 2014), Local Binary Patterns (LBP) (Wang et al., 2006), Histograms of Oriented Gradients (HOG) (Jia et al., 2014), Local Directional Patterns (LDP) (Fei, Wen, et al., 2016), and Local Tetra Patterns (LTrP) (Li & Kim, 2017).

Determining the lines of palmprint in different orientations is an important task, for that reason, many studies used a bank of Gabor filters with different orientations for each pixel. Then, the minimum and maximum filtering responses encoded, corresponding histograms encoded, and finally, compare the templates using a suitable measures. Similar to these descriptors are Local-Line-Directional-Pattern (LLDP) (Luo et al., 2016), LDP texture descriptor (Jabid et al., 2010), and Local-Multiple -Directional-Pattern (LMDP) (Fei, Wen, et al., 2016) descriptors.

Palmprint image features can be extracted in two stages. The first stage involves the coarse-level extraction which is used morphology theory to extract line-like features. The second stage is fine-level extraction where the lines of palmprint examined for predicting positions and directions part by part (Han et al., 2003). Another way for extracting the palmprint features is through the use of Sobel filters with morphology operations (Han et al., 2003). Techniques of hierarchical decomposition (Lin et al., 2005) is applied to extract the principal features of palmprint. From a complex palmprint image, which contains a strong and long wrinkles lines, features extracted through a modified finite random transform method to explicitly extract the principal lines (D. S. Huang et al., 2008).

For palmprint verification, an interactive threshold applied on binarizedpalmprint image to extract some feature points that are lying on the palm lines, separating these points and their line orientations to match and verify the palm (Duta et al., 2002). In a study, Line-like features of palmprintis suggested. In this method, palmprint lines is extracted through using an operator, then the features represented in one dimension feature vector (Han et al., 2003; Kumar et al., 2003).

Sub-space feature learning :Learning algorithms as well as Deep-Learning-based approaches, considered as a part of AI techniques, uses Neural Networks for generate and training a model on set of biometric images called as training set. This model can be used later to predict an image whether it is a genuine or an imposter. In this techniques pre-trained Convolutional Neural Networks CNNs is mostly used to extract features from the image, classifying the templates using specific classifier or can apply a measurement distance to compare the biometric templates. Pre-trained AlexNet, VGG-16, and VGG-19 networks are used for feature extraction from contact-less palmprint images; thereafter, Support Vector Machine (SVM) is used for classification, as applied in (Tarawneh et al., 2018). In another study, pre-trained AlexNet is combined along with SVM to identify newborns using their palmprints through touchless procedure (Ramachandra et al., 2018).

The most common used techniques for reducing dimensions of the image are principal component analysis (PCA) (Connie & Teoh, 2003), fisher's linear discriminant analysis (LDA) (Wu et al., 2003), and locality preserving projection (LPP) (Hu et al., 2007). These techniques are used mainly to represent the most important data that may make image a unique. This is needed to build a large enough database, which is a difficult issue (Connie & Teoh, 2003). DL-based approaches have some limitations. The most important is that they depend on classifiers which are used in supervised training procedures for classification (Genovese & Piuri, 2019).

Table (1): Summary of related works

Category	Method/ Approach/ Algorithms used	Dataset used	Ref.
Texture-based coding	Robust texture-based features method , used the Gabor filter to extract the orientation information	PolyU	(Kong & Zhang, 2004)
	PalmCode method, used a Single Gabor filter to encode every pixel in the image	PolyU	(D. Zhang et al., 2003)
	Competitive-Code method used a multiple Gabor filters as a development to the PalmCode method	PolyU, and CASIA	(Zuo et al., 2010)
	Robust-Line-Orientation Code method	PolyU	(Jia et al., 2008)
	Double-Orientation Code	PolyU& ITTD	(Fei, Xu, et al., 2016)
	Binary Orientation Co-occurrence Vector method used Gabor filters on multiple orientations in every local region	PolyU	(Guo et al., 2009)
	Neighboring Direction Indicator (NDI), paid attention of the neighboring region orientations.	PolyU& ITTD	(Fei, Zhang, et al., 2016)
	NDI and Competitive Code methods integrated in Robust Competitive Code method	PolyU& ITTD	(Xu et al., 2018)
Line-like feature extracting	Extracting the palmprints features using two-dimensional discrete cosine transform (2DDCT)	Contactless DB of Multimedia University (202 palms X 10)=2020	(Leng et al., 2017)
	Scale-Invariant Feature Transform (SIFT)	IITD, CASIA	[21]
	Local Binary Patterns (LBP)	UST	(Wang et al., 2006)
	Histograms of Oriented Gradients (HOG)	PolyU	(Jia et al., 2014)
	Local-Multiple -Directional-Pattern (LMDP)	PolyU, GPDS, &IITD	(Fei, Wen, et al., 2016)
	Local Tetra Patterns (LTrP)	IITD&BERC	(Li & Kim, 2017)
	Local-Line-Directional-Pattern (LLDP)	PolyU& ITTD	(Luo et al., 2016)
	LDP texture descriptor	CK & JAFFE	(Jabid et al., 2010)
	Using morphology theory to extract line-like features, to predict positions and directions of palm line part by part. It used Sobel filters with morphology operations to extract the palm features, and backpropagation neural network for measurement.	Specific DB(50 persons X 30 images)=1500 images	(Han et al., 2003)
	Hierarchical decomposition techniques applied to extract principla line of palmprint.	Special dataset of 4800 images captured from 160	(Lin et al., 2005)

		persons	
	From a complex palmprint image, which contains a strong and long wrinkles lines, features extracted using a proposed method named as modified finite Radon transform.	PolyU(DB1=100, DB2=386)	(D. S. Huang et al., 2008)
	Principal lines and creases extracted using directional masks.	Specific DB(100 persons X 10 images)=1000 images	(Kumar et al., 2003)
Sub-space feature learning	Reducing dimensions of the image like in methods of principal component analysis (PCA).	Specific DB(100 persons X 6 images)=600 images	(Connie & Teoh, 2003)
	Fisher's linear discriminant analysis (LDA).	Specific DB(300 palms X 10 images)=3000 images	(Wu et al., 2003)
	Two-Dimensional Locality preserving projection (2DLPP).	PolyU	(Hu et al., 2007)
	Using pre-trained Convolutional Neural Networks CNNs to extract features and then (SVM) used for classification	MOHI, COEP	(Tarawneh et al., 2018)
	Using pre-trained Convolutional Neural Networks CNNs to extract features and then fusion of (SVM) and a SoftMax classifier are used for classification.	Specific DB(100 palms X 10 images X 2 sessions)=2000 images	(Ramachandra et al., 2018)

Transfer Learning Overview: Earlier at 1996, first publication about the role of generalizing the learned models, especially when training data is scarce (Thrun, 1996). Transfer knowledge from supervised to unsupervised was a goal a studying discovered the famous structure of hypothesis spaces which use a multiple tasks (Ando, 2005). In the related of the above, information bottleneck approach addressed a problem of cross-language classification (Ling & Xue, 2008). Learning performance improved through a special scenario of learning, which applied a heterogeneous transfer learning using data in different features (Yang & Chen, 2009). Traditional algorithm probabilistic latent semantic analysis PLSA is extended to cross-domain text classification algorithm, which aims to use a data (labeled and unlabeled) that are coming from different but related domains, into a unified probabilistic model (Xiao et al., 2010). In the aims of reducing the bias caused by cross-domain algorithm, transfer learning implemented through mapping source domain and target domain into a new space (Tian et al., 2011). Based on the ImageNet dataset, the pretrained features transferability is studied through employing different fine-tuning strategies on several datasets; which led to a wake transferability of features that have high distance between the base and target tasks (Yosinski et al., 2014). Based on the pre-trained AlexNet parameters, transferability described through fine-tuning the network, layer by layer (Donahue et al., 2014).

3. System Motivations And Contributions

Feature extractions using a traditional methods which depend on extract the minimum principal/latent features or those which concern on reducing the dimensionality. Even though these methods have advantages like reducing the computation, but they reduce the performance which is the important measure of biometric system. Especially with contactless-based systems that have a non-constraints on its capturing stage, which make appearance of all features is impossible at every captured image. With another words, due to some reasons like dust, light, temperature, etc. many of features extracted using traditional methods may hidden and weak the quality of image, which leads to losing some features, in order, false rejection rate will increased and performance decreased.

However, using Neural Network which train all features is much more better, where if some not appeared in a single capturing image, there are so many else have been appeared.

This is what motivates us to contribute the current study, to propose a biometric system based on palmprint using CNN transfer learning, which uses a contactless large scale image dataset for apply the training and testing the system, based on pretrained network named as VGG16.

4. Methodology

4.1. Preprocessing:

Dataset preprocessing: the proposed work uses contactless dataset provided from Tongji University, which is named as (large-scale palmviens dataset), which has already captured the subjects and cropped the ROI images. That is to say, it is the base of this work. The preprocessing of the dataset in this work focuses on enhancing images using Gabor filter, blurs it using the median filter, and uses Gaussian and Mean filters for binarizing and generating the last two views of dataset images, to make the dataset capable for as good as possible feature extracting. Figure (1) shows an example of abovementioned processes on a single image.

- a) *Gabor filter*: is a convolutional filter representing a combination of Gaussian and sinusoidal term. Where the Gaussian component provides the weight, and the sine component provides the directionality, Gabor can be used to generate features that may be represented in texture and edges. The formula of Gabor filter can be expressed as:

$$g(x, y, \lambda, \theta, \varphi, \sigma, \gamma) = e^{\left(-\frac{x'^2 + y'^2}{2\sigma^2}\right)} e^{i\left(2\pi\frac{x'}{\lambda} + \varphi\right)}$$

Where,

$$\begin{aligned} x' &= x \cos\theta + y \sin\theta \\ y' &= x \sin\theta + y \cos\theta \end{aligned}$$

g is the Gabor filter generated, (x, y) represent the pixel, λ is the wavelength of the sine component, θ represent the orientation of the Gabor filter, φ is the phase offset, σ is the standard deviation of the Gaussian filter, and γ represent the spatial aspect ratio.

- b) *Median filter* : it is a nonlinear filter, considered as a useful tool used for reducing noise in an image (Gonzalez et al., 2019). Median can be expressed in an equation as:

$$\hat{f}(x, y) = \text{median}_{(s, t) \in S_{xy}} \{g(s, t)\}$$

Where, g is an input image, \hat{f} is the filtered image, S_{xy} is an $m \times n$ subimage (region) of the input noisy image, S indicates that the subimage is centered to the coordinate (x, y) (Gonzalez et al., 2019).

Simply, the median filtering output can be expressed as:

$$g(x, y) = \text{med}\{f(x - i, y - j), i, j \in W\}$$

Where, $f(x, y)$ is the original image, and $g(x, y)$ is the output image, and W is a two-dimensional mask (Zhu & Huang, 2012).

- c) *Adaptive thresholding*: is the method where the threshold value is calculated for smaller regions; therefore, there will be different threshold values for different regions. With the aim of binarizing images and reducing unwanted noise, we apply two forms of thresholding, used for building two separated datasets. These forms are:

- Adaptive thresholding based on MEAN filtering where threshold value is the mean of neighborhood area.
- Adaptive thresholding based on GAUSSIAN filtering where threshold value is the weighted sum of neighborhood values where weights are a Gaussian window.

Dataset arranging: depend on the environment used for implementation dataset must be arranged. In our proposed work we use Tensorflow from Keras tools to implement the system using python environment. So, we arrange dataset to separate each subject alone, randomly divided them into two main sets, training set and testing set, with ratio of 70% and 30% for each respectively. In this consideration, it is important to mention that the validating set is randomly taken as a copy of around 30% from training set for the purpose of testing pre-trained data.

4.2. Convolutional Neural Network

Because of the dataset is designed as a large-scale images, it is convenient, if not necessary, to choose a network that designed for training a large-scale images, which is VGG16. In the following, we explain aforementioned network and how it is applied in our work:

Building the model: as in the VGG16 structure, model built starting of input layer, which is a convolutional Network ConvNet, organized to be RGB channel, so that image passes through stack of convolutional in a small filters, followed by three fully connected layers FC. The final layer is the soft-max layer. All convolutional layers are followed by max-pooling layers with stride of two pixels to prevent the overfitting.

Feature Extracting using VGG16 extractor.

Table (2): Pseudocode Algorithm

<p>Pseudocode Algorithm:</p> <p>Algorithm try to extract principal lines of palmprint.</p> <p>Inputs: An ROI images from TongjiPalmviens dataset</p> <p>Tools: Gabor, median, Gaussian, and mean filters, VGG16 CNN, Matlab17b, and python3.6.</p>
<p>Part1: preprocessing stage:</p> <ol style="list-style-type: none"> 1- Read an image 2- Apply Gabor filter. 3- Smooth an image using Median filter. 4- Segment image using an adaptive thresholding to create a binary image: <ol style="list-style-type: none"> a- Using an adaptive thresholding of Mean b- Using an adaptive thresholding of Gaussian. 5- Repeat above steps to all images in the dataset <p>Result of this part: two datasets extracted from the aforementioned dataset, first used threshold of adaptive Mean and the another thresholded using adaptive Gaussian.</p>
<p>Part2: Arranging datasets (divided data into three sets using different sizes of samples):</p> <ol style="list-style-type: none"> 1- From both sessions, separate images of each subject together (20 images for each palm). 2- Training set: Randomly, choose 70% (14 images) from each palm images. 3- Validation set: From training set, randomly choose 30% (5 images) from every subject in the dataset. 4- Testing set: The remaining are 30% (6 images) for each palm. 5- Repeat above steps for all sets which are created in part1.
<p>Part3: Neural Network modeling, training, and testing:(execution of this part will done for each dataset created in the part1 separately)</p> <p>Step1: using sequential model as:</p> <ol style="list-style-type: none"> 1- First layer: convolutional layer with 32 filters of size 3x3, 'relu' activation, and 'same' padding. 2- Second layer: Maxpooling layer with pooling size of two, and two steps of strides. 3- Third layer: convolutional layer with 64 filters of size 3x3, 'relu' activation, and 'same' padding. 4- Forth layer:Maxpooling layer with pooling size of two, and two steps of strides. 5- Flatten layer. 6- Output layer: a fully connected layer with 'softmax' for activation. <p>Step2: Compiling the model created above with 'Adam' optimizer, learning rate of 0.00001, 'categorical-cross entropy' of loss, and Accuracy of metrics.</p> <p>Step3: fitting the model:</p> <ol style="list-style-type: none"> 1- Train the model using the training data created in part2 2- Validate the model using the validation data created in part2, which are pretrained, because they are a subset of the training data.

Step4: Test the model using untrained data, which is a testing data that arranged in the part2.

Step5: calculate and plot the results:

- 1- Training loss and accuracy.
- 2- Validation loss and accuracy.
- 3- Accuracy of the prediction.
- 4- TAR, TRR, FAR, and FRR
- 5- Imposter and genuine of the verification distribution.

Training stage (Enrollment): the training in the **ConvNet**, is a procedure carried out by optimizing the **multinomial logistic regression objective** using mini-batch gradient descent (based on back-propagation (LeCun et al., 1989)) with momentum.

Testing: At test time, **a trained ConvNet and an input image is given**. It is classified in the following scenario. First, it is isotropically rescaled to a pre-defined smallest image side, which is not necessary to be equal to the training scale. Then, the network is applied densely over the rescaled test image. The fully-connected layers are first converted to convolutional layers. The result is a class score map with the number of channels equal to the number of classes, and a variable spatial resolution, dependent on the input image size. Finally, to obtain a fixed-size vector of class scores for the image, the class score map is **spatially averaged (sum-pooled)**. We also augment the test set by horizontal flipping of the images; the **soft-max class posteriors** of the original and flipped images are averaged to obtain the final scores for the image.

5. Proposed System And Experimental Results

In this section, we will present the contactless biometric system using palmprint recognition. As shown in the framework figure (2), and as the scenario presented in the pseudocode algorithm at table (2), the current study focuses on the contactless palmveins dataset to preprocess high-scale images of dataset to extract palmprint features. Then, a specific neural network is uses to build a model, to train it using aforementioned dataset, and validate the model. Finally, the result is provided, showing a high accuracy contactless biometric system which recognizes an enrolled subject in applicable performance with **96.888% of accuracy for dataset threshold based on the MEAN and 96.166% for dataset threshold based on GAUSSIAN.**

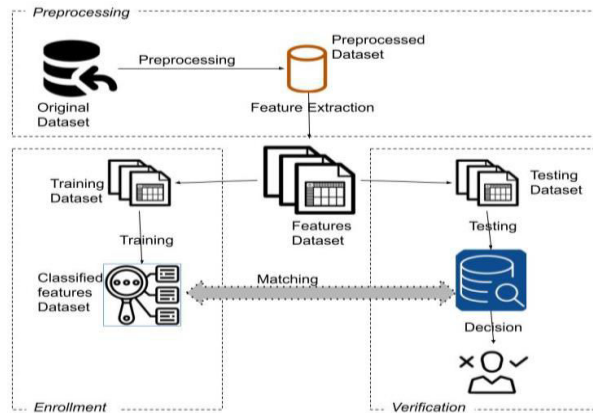


Figure 1: Framework of palmprint biometric system

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 128, 128, 32)	896
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32)	0
conv2d_1 (Conv2D)	(None, 64, 64, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 64)	0
flatten (Flatten)	(None, 65536)	0
dense (Dense)	(None, 600)	39322200
Total params: 39,341,592		
Trainable params: 39,341,592		
Non-trainable params: 0		

Figure 2: CNN Model Structure sample.

Train for 420 steps, validate for 300 steps

Epoch 1/25

420/420 - 1066s - loss: 66.8851 - accuracy: 0.0729 - val_loss: 19.1155 - val_accuracy: 0.3790

Epoch 2/25

420/420 - 762s - loss: 10.4289 - accuracy: 0.5848 - val_loss: 3.1433 - val_accuracy: 0.8013

Epoch 3/25

420/420 - 655s - loss: 1.9174 - accuracy: 0.8668 - val_loss: 0.8260 - val_accuracy: 0.9287

Epoch 24/25

420/420 - 644s - loss: 0.0055 - accuracy: 0.9998 - val_loss: 2.8607e-04 - val_accuracy: 0.9997

Epoch 25/25

420/420 - 639s - loss: 0.0037 - accuracy: 0.9993 - val_loss: 0.5918e-04 - val_accuracy: 0.9997

Figure 4: View of the Training process.

Dataset: A Large-Scale Palmvein Dataset, collected from 300 volunteers from Tongji University (192 males and 108 females). The images were taken in two sessions with six months gap in between. Each session acquired 10 images for each palm of every volunteer, which means that there is large dataset, consisting of 12000 images ($300 \text{ person} \times 2 \text{ palms} \times 10 \text{ images} \times 2 \text{ sessions} = 12000 \text{ images}$). It is a high-quality contactless palmveins dataset (L. Zhang et al., 2018). It is publicly available at <http://sse.tongji.edu.cn/linzhang/contactlesspalmvein/index.htm> (L. Zhang et al., 2018).

The dataset is divided into two parts, first part is an original images with the dimensions of 244×244 , while the another part is the ROI images with dimensions of 128×128 which this research work depends on. Tongji dataset is the most recent dataset in this area. It has the advantage of availability, size – the large number of images, subjects, and in different sessions. These advantages make it reliable for studying and analyzing a variety of biometric traits.

Neural network model: building model is an important issue, it starts with an input convolutional layer with 32 filters of size three, "relu" activation function, and "same" of padding, where the input shape is 128 into 128, which is the size of the ROI image in our dataset. Followed by max-pooling layer with a pool of size two, and two pixels of strides to avoiding overfitting. The second layer is another convolutional layer with 64 filters, and with the same settings on the first layer, except that there is no input shape here because the layer is a hidden layer. This is followed by a similar of max-pooling layer to prevent overfitting. Finally, flatten and dense layers with "softmax" of activation function, to classify the images to specific number of classes (i.e. not binary classes). Figure (3) shows the structure of a similar model.

Feature extraction: using transfer learning, features is extracted based on VGG16 CNN, which is already trained on ImageNet weights. ImageNet dataset is a famous dataset consist of millions of images collected by Google (Z. Huang et al., 2017).

Training: After that, model must be compiled, where its compilation in "Adam" optimization with a learning rate of 0.0001, using measures of accuracy in categorical cross entropy, because of multi classes we are working on. Figure (4) shows a view of the training process. Parameters use is presented in tables (3), with the results mentioned in correspondence.

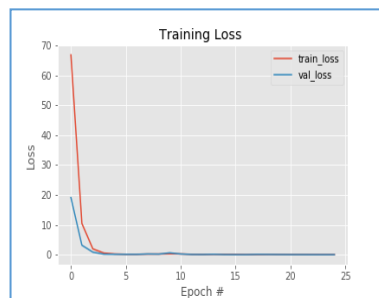


Figure 5: Training and Validation Loss using Adaptive MEAN dataset.

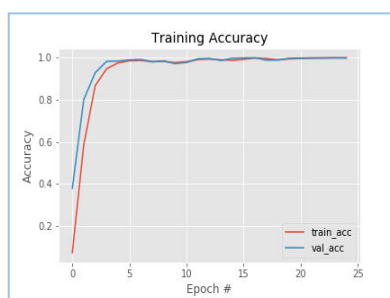


Figure 6: Training and Validation Accuracy using Adaptive MEAN

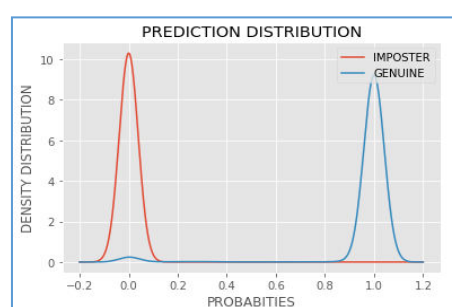


Figure 7: Genuine/Imposter distribution using Adaptive MEAN dataset.

Testing: In testing stage we have to validate the model on some trained data, and then test the model using

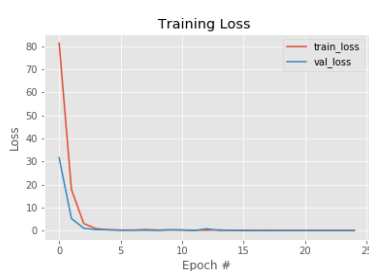


Figure 8: Training and Validation Loss using Adaptive GAUSSIAN dataset.

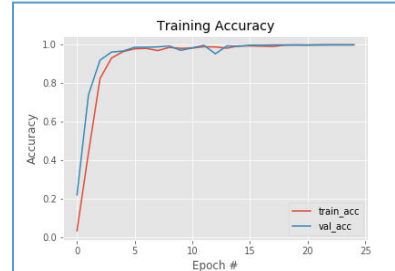


Figure 3: Training and Validation Accuracy using Adaptive GAUSSIAN

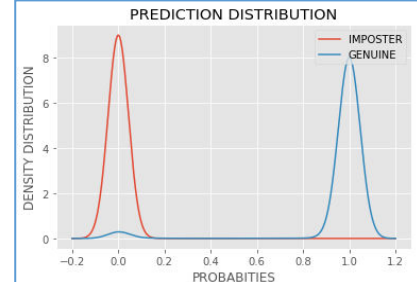


Figure 10: Distribution of Genuine/Imposter using Adaptive

untrained data in the verification phase. In the first phase, called **validation process**, we randomly chose 30% of the trained data and then fitted on the models built above. In this phase, we ensure that the model loss is low and accuracy is high as they are presented in the table (3), and figured out in the figures (5, and 6), where validation accuracy and loss are for pretrained data. The second phase, named verification/test/prediction process, is more important and considered to be the main result of the work. In this phase, untrained images have to be examined on the model. We use our testing set of images which are around 30% of the dataset — untrained before in the model. As shown in the table (3), FPR, FNR, TPR, TNR, and Accuracy of the system are figured out from the

confusion matrix, which is built through this stage. Genuine and imposter figures are plotted in figure (7) for all samples created above.

Here, it should be mentioned that all the above procedure used for dataset threshold based on the MEAN are equally used for dataset threshold base of GAUSSIAN, whose results of parameters and measures are presented in table (3), while the training and validation loss, training and validation accuracy, and genuine/imposter distribution are figured out in figures (8, 9, and 10), respectively.

Table (3): figuration of the Parameters and Results:

Parameter/Metric	Using adaptive Gaussian	Using adaptive Mean	Parameter/Metric	Using adaptive Gaussian	Using adaptive Mean
No. of subjects	600	600	TP	3462	3488
Training images	8400	8400	FN	138	112
Validating images	3000	3000	FP	138	112
Testing images	3600	3600	TN	3462	3488
Total images	12000	12000	TAR/TPR	0.961666667	0.968888889
Training loss	1.4609e-06	0.0037	FAR/FPR	0.038333333	0.031111111
Training accuracy	1.0000	0.9993	TRR/TNR	0.961666667	0.968888889
Validation loss	1.1171e-06	8.5918e-04	FRR/FNR	0.038333333	0.031111111
Validation accuracy	1.0000	0.9997	EER	0.038333333	0.031111111
			ACCURACY	0.96166	0.96888

6. System Evaluation

As presented in the literature, biometric systems can be evaluated under three main categories are data quality, usability, and security.

It is worth to note that based on IOS (El Abed et al., 2013), there are three main points that may help to evaluate the raw data of biometrics are character: which point to the quality of the physical features of the subject, fidelity: a degree of similarity between a biometric sample and its source i.e. between the stored template and new one, and utility: describes the impact of the biometric sample for an individual on the overall performance of a biometric system.

Regarding to the data quality we are using an already dataset which is collected (capturing and ROI cropping) under a standard methods and techniques. So, we just improved the quality of these data in aims to getting a better features as possible.

Based on ISO 13407:1999 (1999), usability is defined as “The extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use”.

Generally, the performance (efficiency and effectiveness) evaluated based on the system type, through metrics testing like FAR, FRR, TAR, TRR, EER, and distribution of genuine and imposter scores. To compare the performance of biometric system, the most metrics used are EER, and distribution of genuine and imposter scores. Which is used to compare the result in the current study with the some similar studies in the literature as presented in the table (4) we can conclude that the current study result is applicable.

Regarding to Users’ acceptance and satisfaction, Many metrics have been defined by the International Organization for Standardization ISO/IEC 19795-1 (2006) (El Abed et al., 2013) in terms of error computations,

time computation, memory allocations, etc. which are provided in the current system and depends on the hardware infrastructure.

In the security side, the International Organization for Standardization ISO/IEC FCD 19792 (El Abed et al., 2013) presents a list of several threats and vulnerabilities of biometric systems like privacy and suggested some recommendations by the evaluators regarding to the security. However, the current system used a large-scale contactless dataset which is hard to fake a similar.

Table (4): Comparison the current system with another studies results:

No.	Dataset used				Performance	Ref.
	Dataset name	Acquisition Type	Subjects size	Images size		
1	<i>PolyU</i>	Scanner palmprint	386	7720	GAR=98.4	(Kong & Zhang, 2004)
2	<i>PolyU</i>	Scanner palmprint	386	7720	FAR=0.04 EER=0.6 GAR=98	(D. Zhang et al., 2003)
3	<i>PolyU</i> , and CASIA	Scanner palmprint Scanner palmprint	386 301	7720 5239	EER 0.041&0.48	(Zuo et al., 2010)
4	<i>PolyU</i>	Scanner palmprint	386	7720	EER=0.4	(Jia et al., 2008)
5	<i>PolyU</i> & ITTD	Scanner palmprint	386	7720	EER=0.0092 &0.0622	(Fei, Xu, et al., 2016)
6	<i>PolyU</i>	Scanner palmprint	386	7720	EER=0.0189	(Guo et al., 2009)
7	<i>PolyU</i> & ITTD	Scanner palmprint Contactless	386 460	7720 2300	EER=0.0254 & 0.0635	(Fei, Zhang, et al., 2016)
8	<i>PolyU</i> & ITTD	Scanner palmprint Contactless	386 460	7720 2300	EER=0.0334	(Xu et al., 2018)
9	IITD,& CASIA	Contactless Scanner palmprint	460 301	2300 5239	EER= 0.4850, 0.4897	[21]
10	<i>UST</i>	Camera capturing	287	5740	EER=0.02	(Wang et al., 2006)
11	<i>PolyU</i>	Scanner palmprint	386	7720	RR=100%	(Jia et al., 2014)
12	<i>PolyU</i> , <i>GPDS</i> , & <i>IITD</i>	Scanner palmprint Contactless	386 460	7720 2300	EER=0.0059, 0.01847& 0.0264	(Fei, Wen, et al., 2016)
13	<i>IITD</i> & <i>BERC</i>	Contactless Mobile camera	460 60	2300 9224	RR=100%	(Li & Kim, 2017)
14	<i>PolyU</i> & ITTD	Scanner palmprint Contactless	386 460	7720 2300	EER=0.0216 & 4.0725	(Luo et al., 2016)

15	Specific DB	Color scanner	50	1500	ACC=98%	(Han et al., 2003)
16	Special dataset	Gray scanner palmprint	160	4800	FAR=0.75	(Lin et al., 2005)
17	PolyU(DB1=100, DB2=386)	Scanner palmprint	100 386	2000 7720	EER= 0.49, 0.565	(D. S. Huang et al., 2008)
18	Specific DB	Digital camera	100	1000	FAR=0.0449	(Kumar et al., 2003)
19	Specific DB	Optical scanner	100	600	ACC=99%	(Connie & Teoh, 2003)
20	Specific DB	CCD-based palmprint device	300	3000	ACC=99%	(Wu et al., 2003)
21	PolyU	Scanner palmprint	386	7720	RR=84.67%	(Hu et al., 2007)
22	MOHL,& COEP	Low-quality(smartphone camera) High-quality	200	3000	ACC=95.5%	(Tarawneh et al., 2018)
23	Specific DB	Contactless(mobile camera)	100	2000	EER=3.03%	(Ramachandra et al., 2018)
24	Tongji large-scale contactless DB	Contactless	600	12000	ACC=96.17% EER=0.0383	Current study
25	Tongji large-scale contactless DB	Contactless	600	12000	ACC=96.88% EER=0.0311	Current study

7. Conclusion

In this paper we designed a contactless biometric system based on palmprint. Using Tongji contactless palmviens dataset, we preprocessed the dataset in two ways. As aforementioned preprocessing, we built dataset with adaptive MEAN thresholding, and adaptive GAUSSIAN thresholding. In the process, we have built a specific convolutional neural network model, trained it, validate it, and then used as verification system to test untrained data from mentioned datasets. Finally, we evaluated the system using an important measures, by calculating the **TPR, TNR, FPR, FNR, EER, and Accuracy** as they are figured out above; we have got a high accuracy recognition system in rate of 96.88% for the adaptive MEAN thresholded dataset, and 96.16% for the adaptive GAUSSIAN thresholded dataset. In the end, we suggest to conduct more studies with various techniques and fusing systems with the aims of gaining a fully accurate system.

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