|| Volume 5 || Issue 12 || December 2020 || ISSN (Online) 2456-0774
INTERNATIONAL JOURNAL OF ADVANCE SCIENTIFIC RESEARCH AND ENGINEERING TRENDS

PALM PRINT RECOGNITION USING INNER FINGER DEEP LEARNING USING NEURAL NETWORK

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Abstract: - Biometric systems based on touch less and less constrained palm print are being increasingly studied since they allow a favorable trade-off between high-accuracy and high usability recognition. Another advantage is that with a palmar hand acquisition, it is possible to extract the palm print as well as the Inner Finger Texture (IFT) and increase the recognition accuracy without requiring further biometric acquisitions. Recently, most methods in the literature consider Deep Learning (DL) and Convolutional Neural Networks (CNN), due to their high recognition accuracy and the capability to adapt to biometric samples captured in heterogeneous and less-constrained conditions. However, current methods based on DL do not consider the fusion of palm print with IFT. In this work, we propose the first novel method in the literature based on a CNN to perform the fusion of palm print and IFT using a single hand acquisition. Our approach uses an innovative procedure based on training the same CNN topology separately on the palm print and the IFT, adapting the neural model to the different biometric traits, and then performing a feature-level fusion. We validated the proposed methodology on a public database captured in touch less and less constrained conditions, with results showing that the fusion enabled to increase the recognition accuracy, without requiring multiple biometric acquisitions.

Keywords: - ***Deep Learning, CNN, Palm print, Finger***

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I INTRODUCTION

Biometric systems are used to recognize individuals based on their physiological or behaviorial traits, without the need to remember passwords (that can be forgotten)or carry tokens (that can be stolen). The most widespread biometric systems consider physio logical traits such as the finger print, palm print, face, or iris, and behavioral traits such as the voice and signature [1]. Among physiological traits, the palm print and the finger surface are being increasingly studied due to their favorable trade-off between high accuracy and high usability [2, 3, 4]. Recently, most biometric systems based on the palm print capture the biometric samples using touchless acquisition procedures, where the surface of the hand does not touch any surface, therefore having high usability, positive social acceptance, and low intrusiveness [3,5]. In addition, it is often possible to capture both the palm print and the inner finger surfaces with a single image of the hand, therefore enabling the use of a multimodal biometric system and increasing the recognition accuracy with a single biometric acquisition. In fact, the use of the inner finger surface in combination with palm print has been proven to often increase the recognition performance [6].

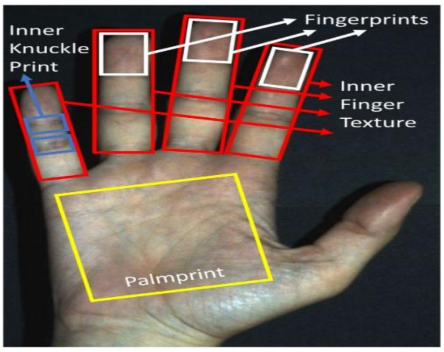


Figure 1.1 Position of the main biometric traits in a palmar acquisition of the hand. In this work, we consider the fusion of the palm print and the Inner Finger Texture (IFT), which can be both extracted from the same palmar hand acquisition

Fig.1.12 shows the position of the palm print and finger areas in the context of hand-based biometric recognition. In this work, we focus on the palm print and on the entire inner surface of the finger, referred to as “Inner Finger Texture” (IFT). In the literature, several works consider the Finger Knuckle Print (FKP) extracted from dorsal hand images, however in this work we consider only the inner finger surfaces since it is possible to extract them from the same palmar hand image as the palm print. Other methods in the literature perform the biometric recognition by focusing on the Inner Knuckle Print (IKP), which represent a specific area of the inner finger surface. However, in this work, we focus on the entire inner surface of the finger [7]. Currently, the majority of methods for biometric recognition based on the palm print or the finger surface are based on local texture descriptors or coding-based methods [2, 7, 8]. However, these approaches consist of handcrafted feature extraction techniques with parameters that may need to be manually tuned for each different database to achieve the optimal recognition accuracy [9].

Recently, Deep Learning (DL) techniques such as Convolutional Neural Networks (CNN) have been increasingly studied in several application fields, including biometric recognition [10], due to their advantages of automatically learning data representations, thus not requiring a handcrafted feature extraction step, and adapting to biometric samples captured in heterogeneous conditions and with less-constrained acquisition procedures [9, 11, 12]. Several recent methods consider DL techniques for biometric recognition using touchless palm print [13, 14, 15, 16] or using features based on the finger [17, 18, 19, 20]. However, current DL methods for palm print and finger recognition use supervised training procedures, extract FKP features from dorsal images of the hand, which require a different acquisition to capture also the palm print, and do not consider the fusion of palm print and IFT. In this work, we propose the first novel method in the literature that uses a DL approach to perform the biometric recognition by fusing palm print and IFT extracted from a single hand acquisition 1. The proposed method has the following advantages: The paper is structured as follows. Section II describes about relevant literature review. Section III describes about Touchless Palmprint and Finger Texture Recognition methodology. Section IV describes about the proposed innovative deep learning technique of Neural Network training tool. Section V presents the experimental evaluation and analysis. Lastly, Section VI concludes the paper.

II RELATEDWORKS

This section introduces the DL-based methods for palm print and IFT recognition. In particular, it is possible to divide DL based methods for palm print recognition in three classes, based on the typology of the used CNN:

1. Methods based on CNNs pretrained on general purpose images;
2. Methods based on CNNs with fixed filters;
3. Methods using CNNs trained on palmprint images.

L. Fei, G. Lu, W. Jia, S. Teng, and D. Zhang, [2] has proposed "Feature extraction methods for palmprint recognition: Palmprint processes a number of unique features for reliable personal recognition. However, different types of palmprint images contain different dominant features. Instead, only some features of the palmprint are visible in a palmprint image, whereas the other features may not be notable. For example, the low-resolution palmprint image has visible principal lines and wrinkles. By contrast, the high-resolution palmprint image contains clear ridge patterns and minutiae points.

The method uses a CNN designed ad-hoc to process the IFT and trained using a supervised procedure to output the class of the corresponding individual. The drawbacks of the considered DL-based methods for palm print and IFT recognition consist in using either supervised training procedures, which require class labels corresponding to the individual during training, and not considering the fusion of the palm print with IFT.In the proposed method of palm print recognition using the Neural Network training tool provides accurate and best results when compared to previous ones.

III INTRODUCTION TO DEEP LEARNING & PALM PRINT RECOGNITION

3.1 Introduction to Deep Learning

Deep learning is a branch of machine learning which is completely based on artificial neural networks, as neural network is going to mimic the human brain so deep learning is also a kind of mimic of human brain. In deep learning, we don't need to explicitly program everything. The concept of deep learning is not new. It has been around for a couple of years now. It's on hype nowadays because earlier we did not have that much processing power and a lot of data. As in the last 20 years, the processing power increases exponentially, deep learning and machine learning came in the picture.

In human brain approximately 100 billion neurons all together this is a picture of an individual neuron and each neuron is connected through thousand of their neighbours.

The question here is how we recreate these neurons in a computer. So, we create an artificial structure called an artificial neural net where we have nodes or neurons. We have some neurons for input value and some for output value and in between, there may be lots of neurons interconnected in the hidden layer.

StepsforperformingDBN:

a. Learn a layer of features from visible units using Contrastive Divergence algorithm.

b. Treat activations of previously trained features as visible units and then learn features of features.

c. Finally, the whole DBN is trained when the learning for the final hidden layer is achieved.

Recurrent Neural Network:
Allows for parallel and sequential computation. Similar to the human brain (large feedback network of connected neurons). They are able to remember important things about the input they received and hence enable them to be more precise.

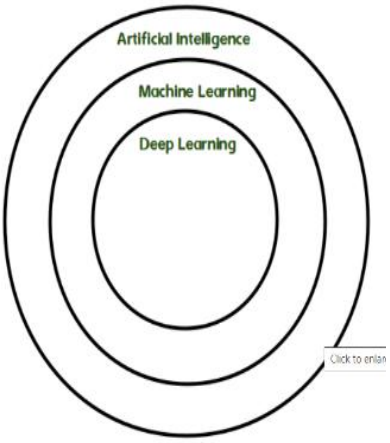
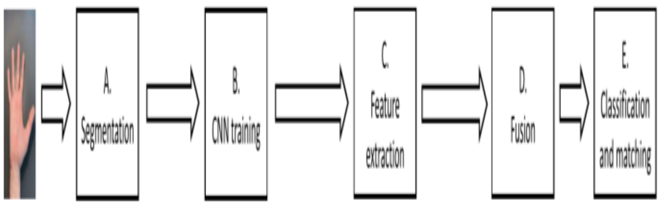


Fig 3.1 Architecture

3.3 Working :
First, we need to identify the actual problem in order to get the right solution and it should be understood, the feasibility of the Deep Learning should also be checked (whether it should fit Deep Learning or not). Second, we need to identify the relevant data which should correspond to the actual problem and should be prepared accordingly. Third, Choose the Deep Learning Algorithm appropriately. Fourth, Algorithm should be used while training the dataset. Fifth, Final testing should be done on the dataset.

IV METHODOLOGY

The proposed approach uses an innovative procedure for the biometric recognition of the hand by performing a feature level fusion of the features computed by a DL model on the palm print and on the IFT. In particular, in this work we consider the PCA Net [24], a CNN trained using an unsupervised procedure based on PCA, applied on the palm print and the IFT extracted from a single hand acquisition. We consider the PCA-based filters since they have been successfully applied for the biometric recognition based on different traits, such as palmprint and face [14, 25].



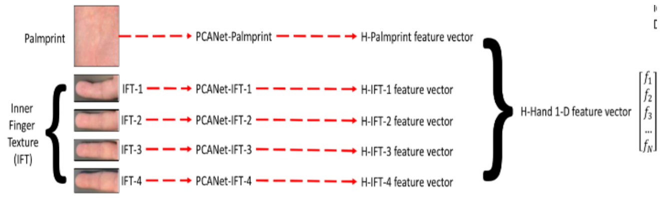


Figure 4.1 Outline of the proposed DL recognition method based on the fusion of palmprint and the IFT.

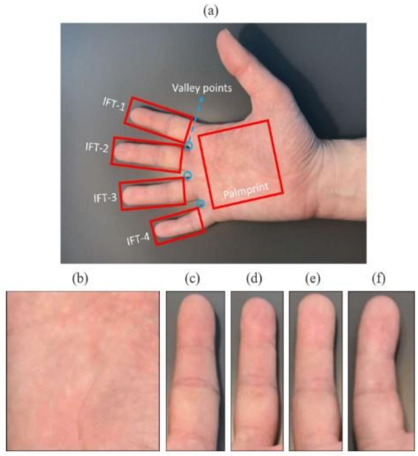


Figure 4.2 Example of the segmentation step to extract the Regions of Interest (ROI) of the palm print and the IFT based on the positions of the valley points.

In this work, we apply the PCANet separately on the five biometric traits, consisting in the palmprint and the four IFT extracted from the index, middle, ring, and little finger, respectively. We consider the five biometric traits separately, instead of considering the whole image at the same time, since the PCA Net requires the training images to be aligned [24]. By considering the whole image to train the PCANet, the four IFT would not be aligned due to differences in the relative positions of the fingers in different acquisitions. Therefore, we use a reference system based on valley points between the fingers to segment and then align the palm print and the four IFT. For each biometric trait, the PCA Net outputs a 1-D feature vector representing the biometric template. Then, we perform the feature-level fusion [26] of the resulting feature vectors to obtain a single biometric template for each hand acquisition. Lastly, we classify the obtained templates using a k-Nearest-Neighbors (k-NN) classifier with based on the Euclidean distance [27].

4.1 Proposed Method of Neural network Palm Print Recognition
Image recognition uses artificial intelligence technology to automatically identify objects, people, places and actions in images. Image recognition is used to perform tasks like labeling images with descriptive tags, searching for content in images, and guiding robots, autonomous vehicles, and driver assistance systems.

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Image recognition is natural for humans and animals but is an extremely difficult task for computers to perform. Over the past two decades, the field of Computer Vision has emerged, and tools and technologies have been developed which can rise to the challenge.

The most effective tool found for the task for image recognition is a deep neural network (see our guide on artificial neural network concepts), specifically a Neural Network (NN). NN is an architecture designed to efficiently process, correlate and understand the large amount of data in high-resolution images.

The human eye sees an image as a set of signals, interpreted by the brain's visual cortex. The outcome is an experience of a scene, linked to objects and concepts that are retained in memory. Image recognition imitates this process. Computers 'see' an image as a set of vectors (color annotated polygons) or a raster (a canvas of pixels with discrete numerical values for colors).

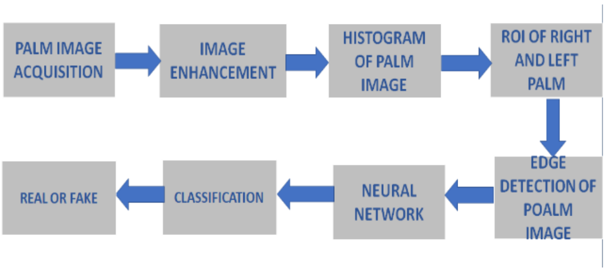


Fig 4.3 Block diagram of proposed system

4.1.1 Image enhancement

Image enhancement is nothing but enhancing the quality of the image by various image processing techniques where the the output is given to histogram section to study the image. Camera or computer image editing programs often offer basic automatic image enhancement features that correct color hue and brightness imbalances as well as other image editing features, such as red eye removal, sharpness adjustments, zoom features and automatic cropping. These are called automatic because generally they happen without user interaction or are offered with one click of a button or mouse button or by selecting an option from a menu. Additionally, some automatic editing features offer a combination of editing actions with little or no user interaction.

4.1.2 Region of Interest

A **region of interest** (often abbreviated **ROI**), are samples within a data set identified for a particular purpose.[1] The concept of a ROI is commonly used in many application areas. For example, in medical imaging, the boundaries of a tumor may be defined on an image or in a volume, for the purpose of measuring its size. The endocardial border may be defined on an image, perhaps during different phases of the cardiac cycle, for example, end-systole and end-diastole, for the purpose of assessing cardiac function. In geographical information systems (GIS), a ROI can be taken literally as a polygonal selection from a 2D map. In computer vision and optical character recognition, the ROI defines the borders of an object under consideration. In many applications, symbolic (textual) labels are added to a ROI, to describe its content in a compact manner. Within a ROI may lie individual points of interest (POIs).

- **Neural Networks**

Neural Networks (NNs) have proven successful in recent years at a large number of image processing-based machine learning tasks. Many other methods of performing such tasks revolve around a process of feature extraction, in which hand-chosen features extracted from an image are fed into a classifier to arrive at a classification decision. Such processes are only as strong as the chosen features, which often take large amounts of care and effort to construct. By contrast, in a NN, the features fed into the final linear classifier are all learned from the dataset. A NN consists of a number of layers, starting at the raw image pixels, which each perform a simple computation and feed the result to the next layer, with the final result being fed to a linear classifier. The layers' computations are based on a number of parameters which are learned through the process of backpropagation, in which for each parameter, the gradient of the classification loss with respect to that parameter is computed and the parameter is updated with the goal of minimizing the loss function.

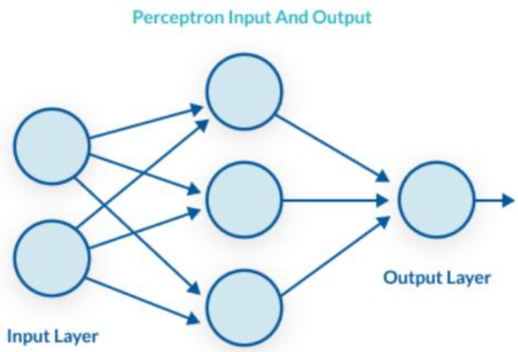


Fig 4.4 Input & Output of image perceptron

- **Normalizing image inputs**—ensures that all input parameters (pixels in this case) have a uniform data distribution. This makes convergence speedier when you train the network. You can conduct data normalization by subtracting the mean from each pixel and then dividing the outcome by the standard deviation.
- **Dimensionality reduction**—you can decide to collapse the RGB channels into a gray-scale channel. You may want to reduce other dimensions if you intend to make the neural network invariant to that dimension or to make training less computationally intensive.

- **Data augmentation**—involves augmenting the existing data-set, with perturbed types of current images, including scaling and rotating. You do this to expose the neural network to a variety of variations. This way this neural network is less likely to identify unwanted characteristics in the data-set.

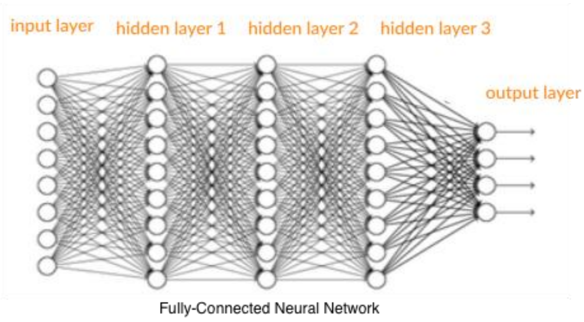


Fig 4.5 Fully connected network

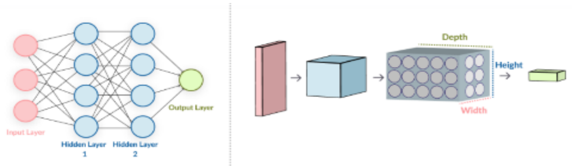


Fig 4.6 Structure of the Neural Network

4.2 Classification and Matching

It is possible to use the proposed approach both in the identification and verification modalities [1]. In the identification modality, we perform a classification step using a k-NN classifier based on the Euclidean distance, with (denoted by 1-NN in the following). We chose a 1-NN classifier since it does not require training and has no parameters to tune. In this way, it is possible to evaluate the ability of the proposed approach to extract a highly discriminative template. In the verification modality, we compute the distance between two hand templates -Hand and -Hand using a matching function -Hand-Hand. In this work, we considered as the Euclidean distance, however different distance measures can be considered.

V EXPERIMENTAL RESULTS

This Section presents the experimental evaluation, by introducing the used database, presenting the error metrics, describing the tuning of the parameters, and then reporting the accuracy obtained using our approach. To evaluate the accuracy, we performed a technology evaluation [34] and compared the recognition performance of our method against other methods in the literature based on CNNs. One partition of the ROIs is used for training and the other partition for testing, with disjoint sets of individuals in the training and testing subsets. We performed the feature extraction, fusion, classification, and matching steps on the testing subset. Then, we averaged the results on the iterations. We evaluated the performance of the proposed approach both in the identification and verification modalities. In the identification modality, we perform a classification using the 1-NN classifier based on the Euclidean distance, applied on the feature vectors computed from the testing subset. As the error measure, we consider the classification accuracy, expressed as the percentage of correctly classified samples. In the verification modality, we used the matching algorithm based on the Euclidean distance to compute the distances between the different templates. For each individual, we selected templates as enrollment and the considered the other templates as testing [38].We chose the size of the palmprint ROI as and the size of the IFT ROI as . D. Recognition Accuracy We compared the accuracy of the proposed method against pretrained CNNs used as feature extractors. We used the features extracted from the sixth fully connected layer [21].

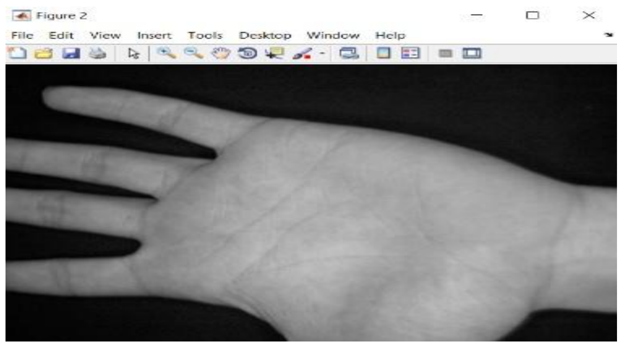


Fig 5.1 Original Plam image

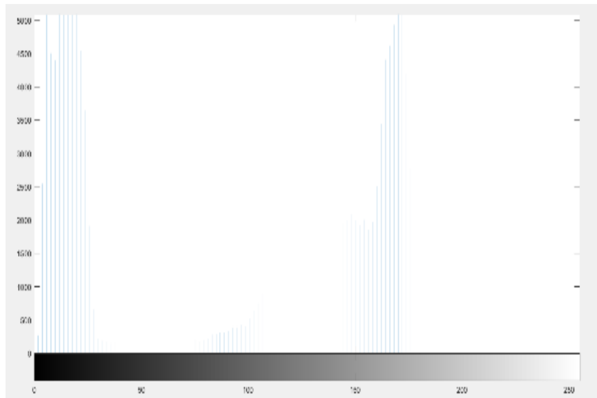


Fig 5.2 Histogram of original palm image

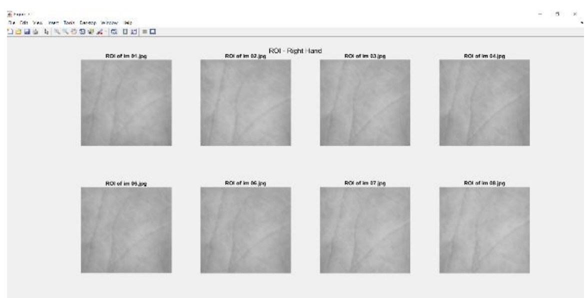


Fig 5.3 Region of interest of palm image (Right)

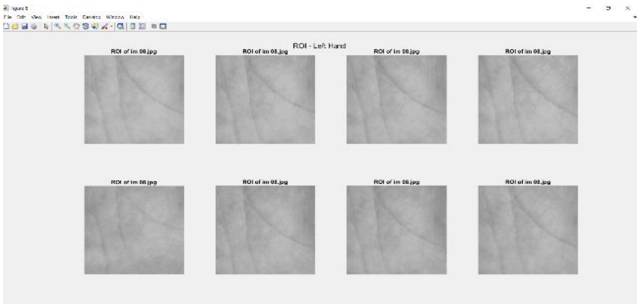


Fig 5.4 Region of interest of palm image (left)

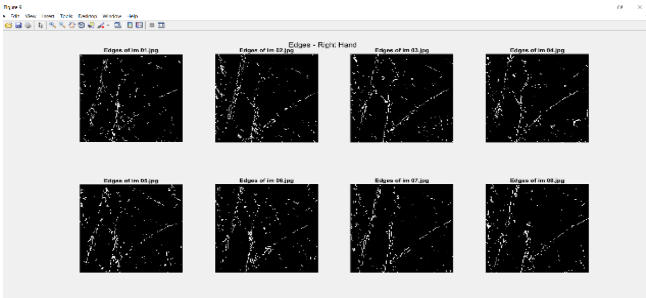


Fig 5.5 Edges of palm image (Right)

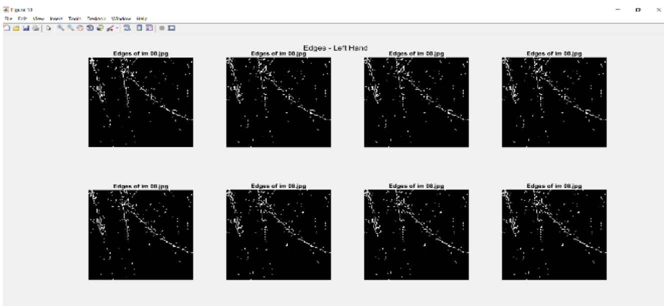


Fig 5.6 Edges of palm image(Left)

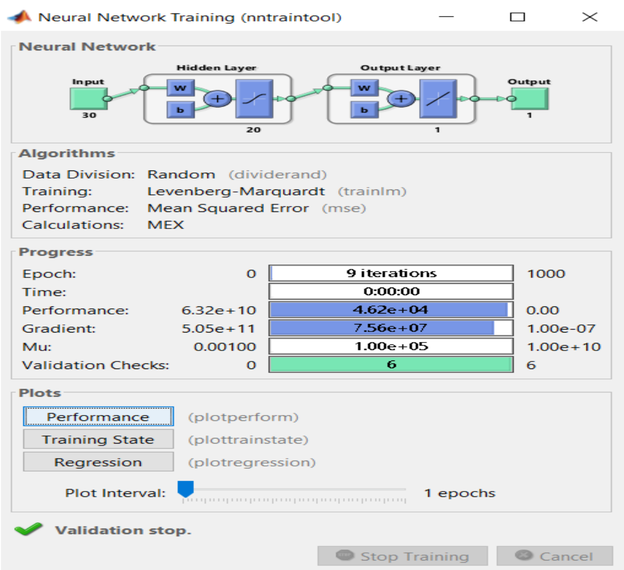
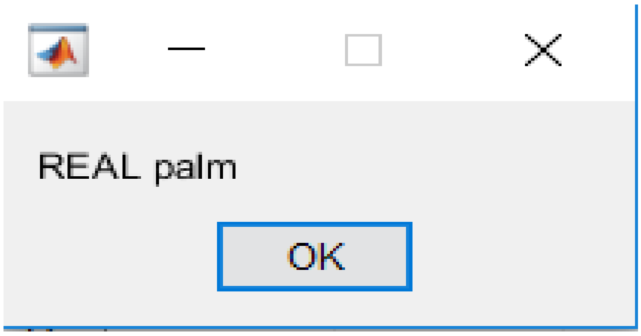


Fig 5.7 Neural Network Training Tool



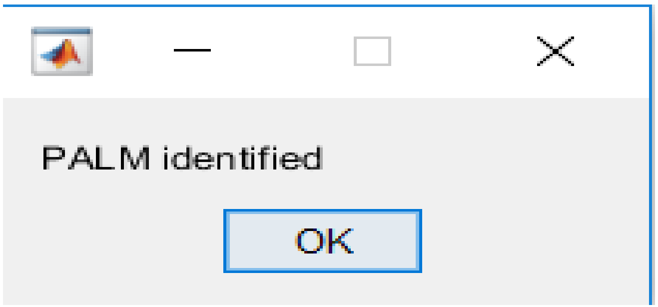


Fig 5.8 Palm identification

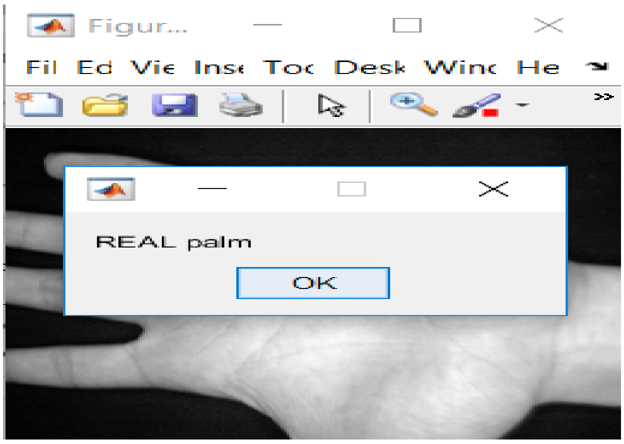


Fig 5.9 Palm Recognition

VI CONCLUSIONS

In this paper, we proposed the first novel method in the literature based on DL for the fusion of the palmprint and the IFT using a single hand acquisition. The method is based on a novel use of the PCANet, a CNN trained using an unsupervised procedure, which is applied separately on the palmprint and on the IFT, and on a feature-level fusion of the resulting feature vectors. We evaluated the proposed approach on a database of hand images captured with high variations in the position and orientation of the hand. The use of the proposed approach always allowed increasing the recognition accuracy of the biometric procedure, with respect to using the palmprint or the IFTs separately. Future works should consider the use of segmentation algorithms to extract the hand even in images captured with unconstrained backgrounds, as well as other classifiers and different distance measures.

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