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Palmprint Authentication Technique Based on Convolutional Neural Network

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Abstract: A palmprint is a small part of the palm flat that contains additional characteristics that can be used in authentication systems. It also has the property of permanence, which indicates that it will not alter through time. However, extracting the deepest and useful features from palmprint is a critical point. Most of the recently developed methods use principal lines, wrinkles, and creases, which is not enough to distinguish two people due to closeness. Recently, deep learning methods have been considered as an important key point for these kinds of tasks in order to extract deep features like texture features. We present a deep convolutional neural networks (CNN) that is specifically designed to suit palmprint images in order to achieve secure authentication processes. The COEP palmprint database was used in the experiments, and the accuracy measure as well as the F1-score were used in the evaluation process. The proposed model had a high level of accuracy, with a score of 97.55 percent. Palmprint authentication is performed efficiently using the described method.

Keywords: Palmprint, Biomertic, Deep Learning, Convelutional Neural Network, Authentication

1. Introduction

Due to the obvious rising number of frauds and scams, security and surveillance has been a major concern in recent years. In addition, many access control systems, particularly older techniques such as passwords or personal identification numbers, have seen certain violations and compromises. To evade such violations, modern society has turned to more dependable ways, such as biometric methods, to give more security in human identity and verification. Fingerprint, voice, palmprint, iris, face traits, hand vein, EEG signal and other biometric technologies have been created. The recognition technique works by recording a sample of a feature, such as a digital photograph of the fingerprint, and then transforming the sample into a biometric template using some sort of mathematical function. The biometric pattern will represent the feature in a normalized, effective, and highly discriminating manner, which may subsequently be compared to other templates to ascertain identification [1]. This study proposes a method for authenticity that uses a palmprint since it has several features that can be employed in the matching process, such as a large area of interest, is unaffected by age, and has a high level of user approval.

Palmprint is an accepted biometric technology, as with face, fingerprint, iris, and vein. [2]. It is a small part of the palm surface that carries more particulars that are suitable for personal authentication technique, and it also has a specific property known as permanence, which means it will not change over time [3]. Palmprint authentication has many benefits that make it more appropriate for practical uses in real world, such as low-cost image gathering equipment's, usage with both high- and low-resolution images, and differences features like as grooves and crinkles [4].

Several recent studies have looked into palmprint authentication using various methods. Kumar and Premalatha [5] introduced a procedure based on a mixture of local and global data. The discrete orthonormal The Stockwell transform is adopted to gain the enhanced palmprint's local features, the Stockwell transform is useful for the analysis of palmprint image because it preserves phase information by linear frequency scaling, while the scale of the discrete orthonormal Stockwell transform is reduced to infinity to gain global features, and it provides advantageous and supplementary information about spectra that is not available from locally referenced phase information in the continuous wavelet transform (CWT). Their methodology is tested on databases from PolyU, COEP, and IIT Delhi since where this mixture of local and global features produced good results. Fei et. al. [6] introduced a convenient and straightforward double half-orientation-based mode approach for feature extraction and authentication of palmprints. A group of "half-Gabor" filters is defined in

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their method for palmprint half-orientation extraction. The dual half-orientations characterize the global orientation characteristic of a palmprint more appropriately than the monocular dominant orientation. Besides that, Ma et. al. [7] proposed (DOSFL) method for palmprint authentication. The Hamming distance is used to code match DOSFL, which uses four code bits to describe both the direction and scale characteristics of a palmprint, through incorporating discriminant analysis into the palmprint coding process. They also present a palmprint authenticity approach based on discriminant learning that has multi-orientation and multi-scale properties (MOSDL). The trials used two datasets, with average recognition rates of 98.05 present and 97.63 present. Correspondingly Dubey and Kanumuri [8] presented proposed a method for extracting energy signatures in various orientations using oriented exponential wavelets. The bidirectionally twirl directed energy signatures are then used to generate the directed structural energy signature codes. Four datasets are PolyU, IITD, PolyU multispectral, and PolyU ver. II were used to test the effectiveness of the suggested strategy, and the findings were good. Verma and Chandran [9] also propose a palmprint verification model based on ”Sobel Edge Detection, a 2D Gabor Filter, and Principal Component Analysis (PCA)”. The model is validated using the IITD palmprint database. The obtained results were 99.5 present accurate. Kadhm et. al. [10] suggests employing a Palmprint Recognition System named (PRS). The system makes use of orientation, Local Binary Pattern (LBP) characteristics, and the K-Nearest Neighbor algorithm (KNN). The model achieved a recognition rate of 99.7 percent by using two palmprint image databases, the COEP and CASIA datasets. Wang et. al. [11] attempted to generate high quality palmprint images using a deep learning method based on an enhanced Deep Convolution Generative Adversarial Net (DCGAN) by swapping the convolution transpose layer with linear upsampling and incorporating the Structure Similarity (SSIM) index into the loss function. Experiment results on two publicly available datasets, the IIT Delhi and CASIA palm databases, demonstrate the efficacy of their proposed strategy. Based on the existing studies that shown the significance of deep learning models, we propose a palmprint authentication model technique that makes use of deep convolutional neural networks (CNN) to achieve high accuracy based on deep features. The following points summarize and justify the paper’s importance and contribution:

- Conventional methods focus on basic properties such as lines, wrinkles, and creases, which are unable to effectively distinguish two people owing to closeness, whereas our proposed method extracts the palm’s deepest features.
- Previous palm techniques relied on direct contact between the palm pattern and the capturing system device, which could limit user acceptance. As a result, our research has centered on contact-free solutions, which minimize the requirement for physical interaction while still improving comfort and health.
- CNN has had recent success in a variety of sectors, including biometrics. The vast majority of deep learning models, on the other hand, necessitate a huge dataset to analyze and train the neural network, however our method can operate with a smaller dataset.

According to the over mentioned issues, our objectives are to provide a deep network-based approach that increases accuracy, lowers the cost of the biometric system, effective with little data, and enhances user acceptance by focusing on only the most important characteristics of the image. The remainder of the paper is orderly as follows: Section 2 provides theoretical context; Section 3 explain the proposed approach; Section 4 displays and discusses the experimental results; and Section 5 concludes the paper.

2. Theoretical Background

This section describes the general palmprint authentication technique, followed by a brief explanation of convolutional neural networks (CNN).

A. *Palmprint Authentication Procedure in General*

As shown in Fig. 1, a typical palmprint authentication system has five components: palmprint receiving, preprocessing, region of interest extraction (ROI), features extraction, matching and decision.

B. *Convolutional Neural Network*

Deep Learning are Artificial Neural Networks (ANN) with multiple layers. One of the most widely used deep neural network is the convolution neural networks (CNN). CNN has several layers, of which convolutional layers, pooling layers, and fully connected layers (FC), as illustrated in Fig. 2. CNN performs admirably in terms of machine learning issues. The applications dealing with images data, such as (Image Net), natural language processing (NLP), and computer vision, were particularly impressive. The first layer of CNN is convolution, which has a group of filters. They’re called filters because they operate like traditional image processing filters. The convolutional neural network, on the other hand, initializes these filters to make them more suitable for the task at hand. It is feasible to addition further layers next the input layer to make this method more beneficial. More filters can be assigned to every layer. As a result, we may extract several features from the image. It also has many adjustment options, including stride, padding, and an activation function [12]. The computations for this layer can be explained using Equation 1 [13].

$$M_{n,k,c^l} = B_c^l + \sum_{i=-r_h^l}^{r_h^l} \sum_{j=-r_w^l}^{r_w^l} \sum_{c^{l-1}=1}^{c^{l-1}} W^{c^l}_{i+r_h^l,j,r_w^l,c^{l-1}} M_{u+i,k+j,c^{l-1}} \tag{1}$$

where: M_{u,v,c^l} is the convolution layer’s output, *(n,k)*

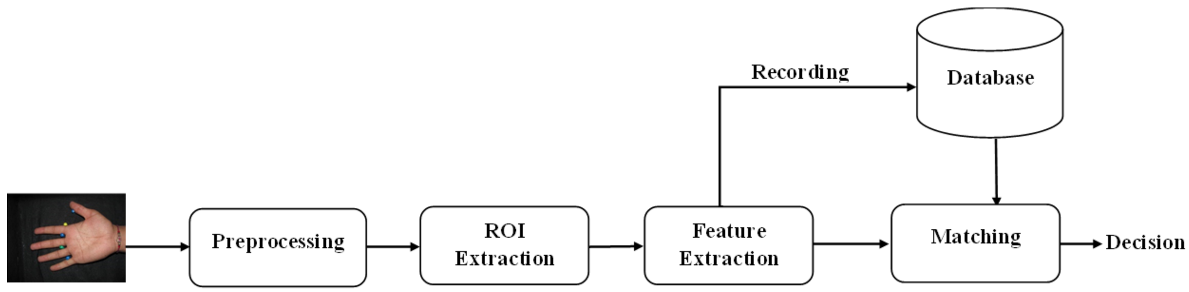

Figure 1. The standard structure of the palmprint authentication procedure

represents a pixel coordinate, B_c^l is a channel bias, $W_{i,j,c^{l-1}}^{c^l}$ is the filter weighs, r_w^l and r_h^l are the width and height of the convolution layer kernal, respectively. C is the channel number, l is the current layer, and *l-1* is the before layer, c^{l-1M} is the output of the previous convolution layer of the channel c.

Pooling is the next layer following convolution. The basic goal of pooling is to reduce the complexity of subsequent layers by down-sampling. It's comparable to lowering the resolution in the context of image processing. Pooling has no effect on the filters number. Max-pooling is one of the most popular kinds of pooling strategies. It divides the image into sub-area rectangles and returns only the highest value of each sub-inside. Equation 2 [14] can be used to demonstrate the maximum pooling calculations.

$$p([u_l^f]_{n_l}) = MAX[u_l^f]_{n_l} \tag{2}$$

where: $p([u_l^f]_{n_l})$ is the pooling layer output, $[u_l^f]$ is the feature set, n_l is the pooled window dimension, l is the current layer, f is the feature.

The FC layer, which is the final layer, is comparable to how nodes are placed in a traditional neural network. So, each node in a FC layer is directly coupled to every node in the preceding and subsequent layers. However, a fully-connected layer has a much of parameters that require complicated computing in training. As a result, the dropout technique [12] can be used to reduce the nodes number and connections. The computation of this layer is represented by Equation 3. [13].

$$f_r = \sum_{x=1}^{n_1^{l-1}} \sum_{y=1}^{n_2^{l-1}} \sum_{z=1}^{n_3^{l-1}} W_{x,y,z,r}^l Q(c)_{x,y}, \forall 1 \leq r \geq n^l \tag{3}$$

where: f_r is the output of the FC layer, n_1^{l-1} represents the width of the preceding channel, n_2^{l-1} indicates the height of preceding channel, n_3^{l-1} denotes the number of preceding channels, $Q(c)_{x,y}$ symbolizes pooling layer outputs vector, $W_{x,y,z,r}^l$ is the weights between the pooling

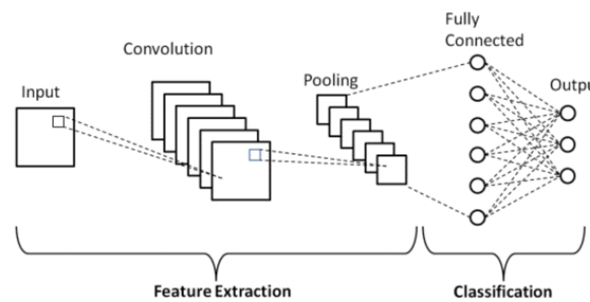

Figure 2. The convolutional neural networks model structure

and FC layers, and n^l is the required number of classes. The basic structure of CNN model is shown in Fig. 2.

3. The Proposed Palmprint Authentication Technique

In this section, we describe the proposed palmprint authentication technique, that involves two major stages: determining the region of interest (ROI) and extracting and matching features using the CNN model. Fig. 3 illustrates the proposed palmprint authentication technique.

A. Region of Interest Extraction

Before extracting palmprint features, the region of interest (ROI) of palmprint images must be segmented. In this paper, we adopted the method proposed by [15] as the region of interest method.

The ROI is calculated using a number of principles. Setting up the coordinate system based on the spacing among fingers is the most common rule for locating ROI. Initially, a low-pass Gaussian filter is used to smooth out the noise in the input palm print images. The smoothed palmprint image is then directly thresholder to produce a binary images, from which the palmprint boundary is determined using a boundary tracking algorithm. Then, reference points are located at the bottom of the gaps among the index and middle fingers, as well as among the ring and little fingers, on the boundary. Next, the perpendicular bisector of the line segment among two reference landmarks is set up to locate the position of ROI. Lastly, the subimage is cropped and resized at a specific location; the ROI of the palmprint image in this paper is set to 192×192 pixels [15]

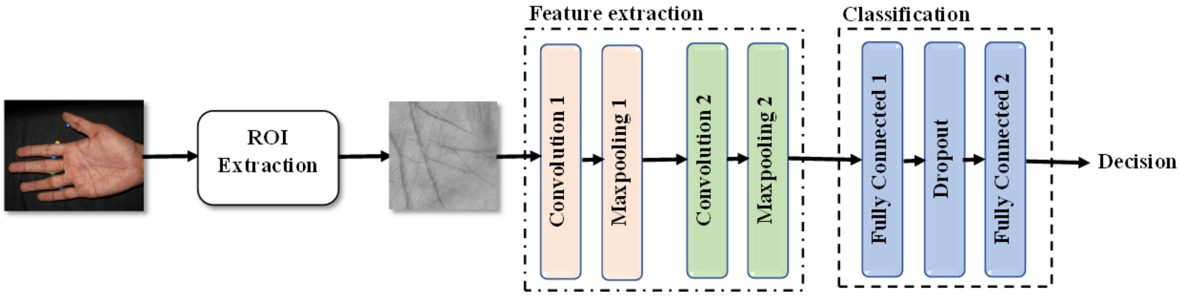

Figure 3. The proposed palmprint authentication technique components

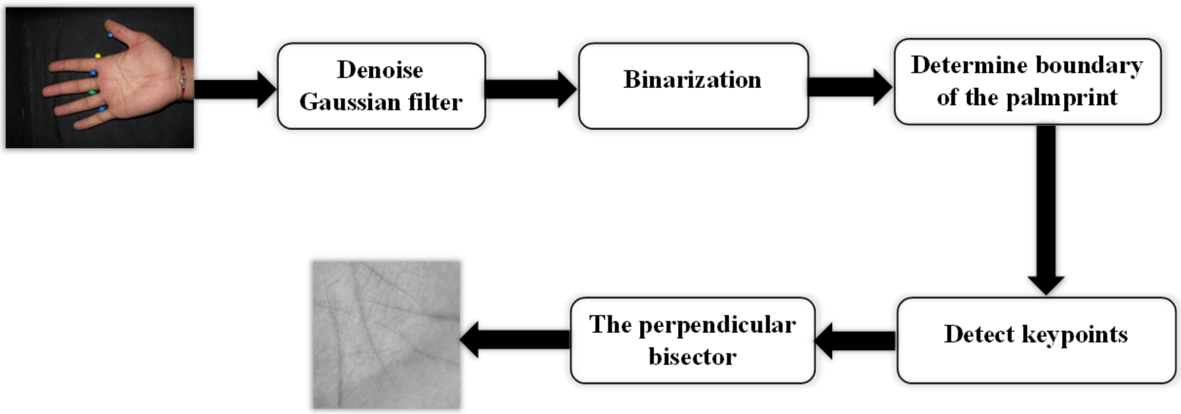

Figure 4. The region of interest extraction steps

[16]. The ROI steps can be summarized as shown in Fig. 4.

B. *Feature Extraction and Matching via Convolutional Neural Network*

This section goes over the various layers that appear in the proposed CNN-based model, which we developed and built specifically for palmprint images. The model is composed of multiple layers. Layers include the input, convolution, activation function part (LeakyReLU), pooling, fully connected, dropout, and output. The input layer is initially set up to receive a gray-scale ROI palmprint image with a resolution of 192×192 pixels. The convolution layer is then used. Two convolution layers are proposed. The features of the grayscale palmprint image can be analyzed using these layers. Each convolution layer has a rectifier linear unit (LeakyReLU) activation function, which is also a piecewise activation function based on the ReLU concept. Only when the input value is negative is there a difference. Instead of zeroing the value like ReLU does, Leaky ReLU multiplies it by a tiny integer α (generally 0.01). As a result, the negative section receives a value, although a very small one. It's an attempt to find a solution to the dying ReLU problem. The pooling layer is applied after each convolution layer. By using windowing and maximum operations, this layer can minimize the size of the data. After that, a fully connected layer is used. This layer adjusts to the number of units in the preceding layer and the number of Categories that are required. After the fully connected layer, we add a dropout layer to create a model that is more general and far less probable to overfit the training data. Finally, we add a final layer made up of Softmax functions, which are commonly employed for multiple classification issues. This layer has been modified to accept the number of categories.

The ideal size of the proposed CNN design is determined empirically by gradually increasing the number of convolutions and max-pooling, followed by the number of filters, and finally selecting the network with the best performance. Table I summarizes the proposed CNN architecture. In addition, the final structure of the proposed CNN model can be described by the Fig. 5.

4. Experimental Results

The proposed palmprint authentication technique is implemented on a GPU Nvidia Tesla k80 12GB processor with 13GB of RAM using Google Colab, which provides Python3 in a free environment. Moreover, MATLAB v13.a is utilized to extract the region of interest. The suggested technique's performance is assessed using the COEP Palmprint Database, taken from the College of Engineering, Pune-411005, and the entire proposed authentication technique is assessed by of F1-score and accuracy.

TABLE I. SUMMARY OF THE PROPOSED CNN MODEL ARCHITECTURE

Layer Kind	Filter Size	Activation Function	Kernel	Units	Input shape	Output shape	Parameter
Convolution	3x3	LeakyReLU	12	-	192,192,1	190,190,12	120
Max pooling 2D	6x6	-	-	-	190,190,12	31,31,12	0
Convolution	3x3	LeakyReLU	12	-	31,31,12	29,29,6	654
Max pooling 2D	4x4	-	-	-	29,29,6	7,7,6	0
Flatten	-	-	-	-	-	294	0
Fully connected	-	LeakyReLU	-	512	-	-	151040
Dropout (rate = 0.5)	-	-	-	512	-	-	0
Fully connected	-	Softmax	-	163	-	-	83619
Total params:	235,433						
Trainable params:	235,433						

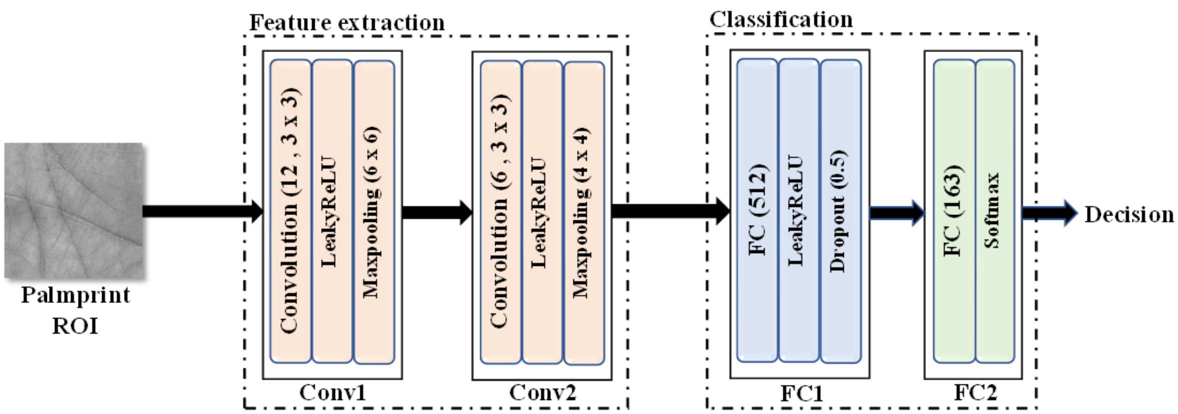

Figure 5. The proposed CNN model architecture

A. COEP Dataset

The palm images in this database were taken with a CanonPowerShot SX120 IS camera, with a resolution of 1600×1200×3 pixels and an image density of 180 dots per inch, according to the file's features information (DPI). The database was compiled over one year, and the downloaded collection contains 1304 images of 163 palms, with 8 images per palm [17].

B. Region of Interest Extraction Results

We used 1304 images from the COEP dataset to extract ROIs using [15], with each extracted ROI image having a size of 192×192 pixels and resulting in a grayscale image. We split it into two parts: 75 percent for training and 25 percent for testing, with different data for the same person being utilized in each. In Fig. 6, different ROI palmprint photos from different people's training and test sets are exhibited.

C. Evaluation Metrics

This work evaluates the proposed technique using accuracy and F1-score metrics. The first metric is accuracy which is defined by Equation 4.

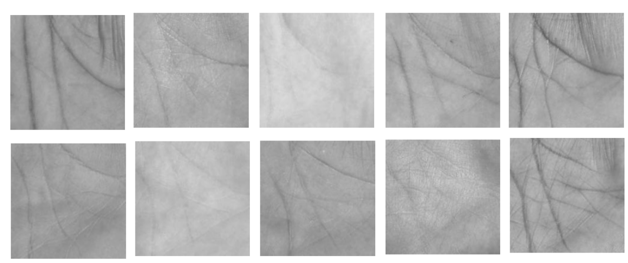

Figure 6. Samples of ROI extracted palmprint

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

Where TP (true positives) is the number of palmprints that are correctly and classified correctly, TN (true negatives) represents the number of palmprints that are incorrectly and classified incorrectly, FP (False positives) denotes to the number of palmprints that are incorrectly and classified correctly, and FN (false negatives) indicates the number of palmprints that are correctly and classified incorrectly. The F1-score is the harmonic mean of precision and recall, and it is calculated as follows 5.

$$F1 - score = \frac{2PR}{P + R} \quad (5)$$

Precision and Recall are two evaluation measurement used to evaluate the techniques performance, which are represented in Equations 6 and 7.

$$Precision = \frac{TP}{FP + TP} \quad (6)$$

$$Recall = \frac{TP}{FN + TP} \quad (7)$$

D. Performance of Assessing the Proposed Technique via Accuracy and F1-Score

The ROI was recovered and divided into 978 palmprint images to training and 326 palmprint images to testing. The network is then trained on the popular deep learning platform Keras, with the classification function defined as the Softmax function, each convolution layer's weights initialized using the LeakyReLU function, and 100 epochs of training. Many experiments were set up and analyzed in order to determine the right model parameters. After multiple rounds of training, the best accuracy rates were 97.55 present when the kernel in the first convolution was 12 with Maxpooling 6×6 and the kernel in the second convolution was 6 with Maxpooling 4×4. The results of evaluating various network parameters are displayed in Table II In this table, the parameters of the convolution and pooling layers are fated one by one, by tweaking one parameter and settling the values of the others. Furthermore, using the ReLU function results in the dying ReLU problem, which is defined as a situation in which a neuron becomes inactive and stuck there, particularly in the first few layers, because no backpropagation can take the neuron out of it. The reason for this is that the accuracy of our model reduced to 0.61 percent when we utilized the ReLU function.

Fig. 7 also depicts the relationship between the proposed network's accuracy and the number of iterations used during the training phase.

From the Fig. 7, we can notice the start of the accuracy with a slight increase. Until there is a dramatic rise after epoch 20. After that, the indicator begins to gradually increase at epoch 40, and the accuracy of access is relatively stable after epoch 80.

E. Evaluate the Whole Model Using Grad-CAM Result

We used a Gradient Weighted Class Activation Map (Grad-CAM) in this part to show places of interest in the final convolutional layer and the Softmax activations output from the model. The GRAD-CAM has established the particular areas of the palmprint that CNN considers important to discriminate between classes (as shown in Fig. 8 for some samples). In order to make the classification choice, the network focuses on the sections indicated in yellow, which represent the essential points in the palm image, and red, which denotes the least important points, as seen in the Fig.8.

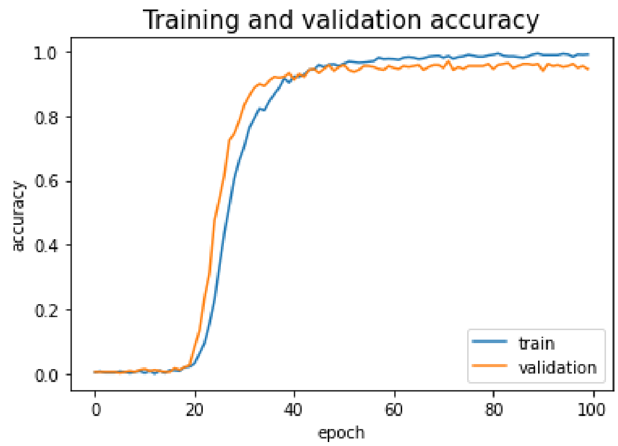

Figure 7. The accuracy of the proposed model

F. Visualization of Convolution Layers Using Feature Maps Technique

In this section, the feature maps technique is adopted to show the applied filters for a single image. Fig. 9 shows the visualized six filters. It includes a diagram with six rows of three images for each filter. Dark regions represent little or inhibitory weights, while light regions represent big or excitatory weights.

Additionally, we employ the feature maps technique to evaluate and comprehend the model's predictions. The former method aids in comprehending how the model learns different filters and how the input is passed via the layers. The assumption is that the feature maps near the model's input detect tiny or fine-grained details. whereas feature maps near the model's output capture more general details Fig. 10 depicts the feature maps for the first convolution layer, which has 12 filters. The figure below shows that the outcome of applying the filters in the first convolution layer yields various types of features.

Moreover, Fig. 11 shows feature maps for the second convolution layer for individual image, which contains 6 filters. We can see that the model works deeply where the feature maps show fewer details. This context is expected from this convolution level but has the ability to give good features that might be used for classification. We generally lose the capacity to interpret these deeper feature maps, but they are unmistakable for the model.

5. Conclusions

In this paper, we concentrate on palmprint authentication using deep learning, specifically the CNN technique. The challenge of palmprint image authentication, as described

TABLE II. THE RESULTS OF ASSESSING DIFFERENT NETWORK PARAMETERS

Filters in Conv1	Maxp.1	Filter in Conv2	Maxp.2	Activation function	Hidden layers	Acc.	F1-score
20	6x6	15	4x4	LeakyReLU	1x512	96.32	95.40
15	6x6	10	4x4	LeakyReLU	1x512	94.48	96.63
12	6x6	6	4x4	LeakyReLU	1x512	97.55	96.63
12	4x4	6	2x2	LeakyReLU	1x512	93.25	93.87
12	4x4	6	4x4	LeakyReLU	1x512	93.87	95.09
12	6x6	6	6x6	LeakyReLU	1x512	90.80	91.72
12	6x6	6	4x4	ReLU	1x512	0.61	0.61
12	6x6	6	4x4	ELU	1x512	95.71	95.40
12	6x6	6	4x4	Swish	1x512	95.09	95.40
12	6x6	6	4x4	Leaky ReLU	1x256	96.93	96.32
12	6x6	6	4x4	Leaky ReLU	2x256	92.64	93.25

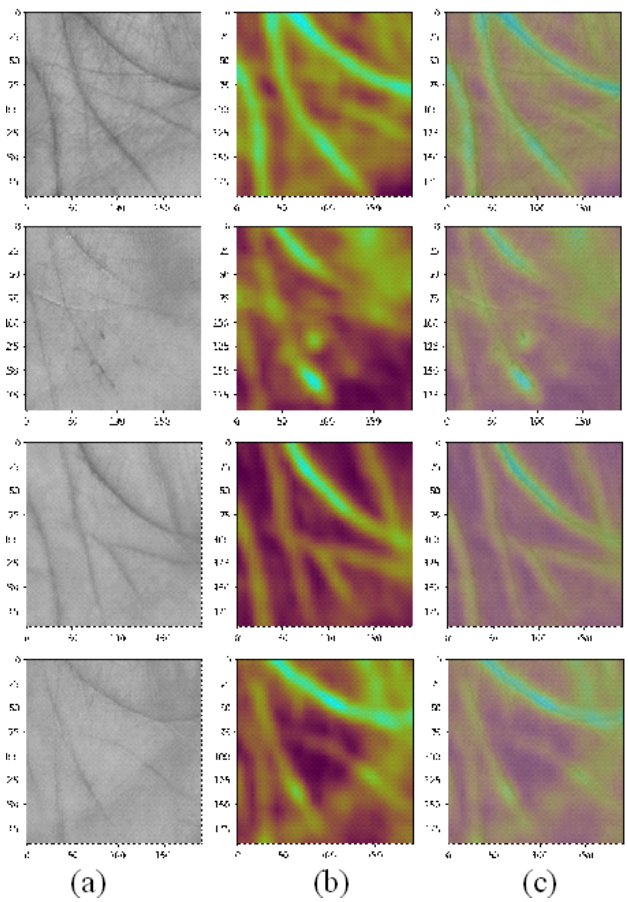

Figure 8. Illustration of the GRAD-CAM from the model: (a) original image (b) points of interest in the final convolutional layer (c) Softmax activation output

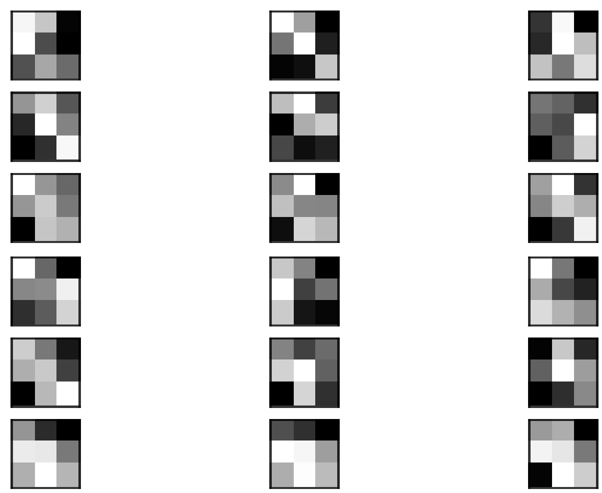

Figure 9. Feature map technique for illustrating filter interpretability

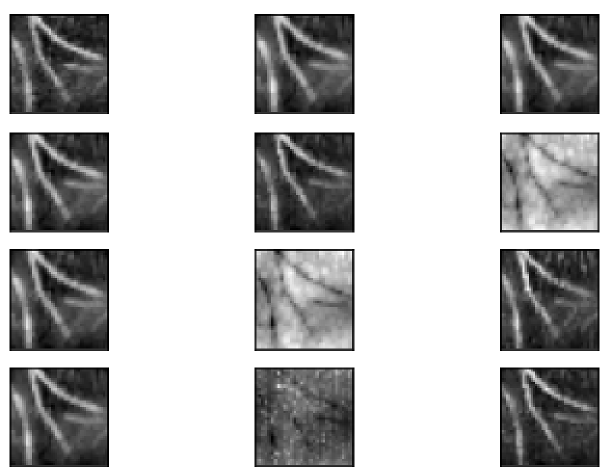

Figure 10. An illustration of the first convolution layer, which contains 12 interpretability filters based on the feature maps technique.

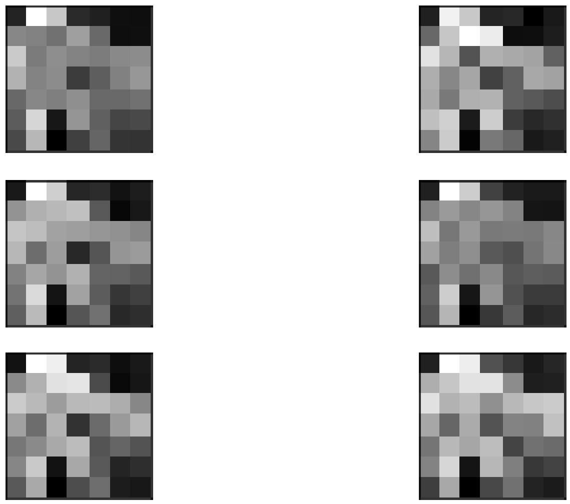

Figure 11. An illustration of the second convolution layer, which contains six interpretability filters based on the feature maps technique.

in this research, is to obtain deep features that lead to valuable authentication results. On COEP's publicly available datasets, the training procedure was fine-tuned. Several experiments have been carried out to investigate how the parameters of various networks layers of CNN change. We acquired deep features from the CNN model using the suggested approach, which resulted in significant authentication results with a fewer number of images, which is a major issue in any deep learning model. The model has demonstrated that it can adapt to a wide range of palmprints, resulting in excellent authentication. The best results obtained were 97.55 percent accuracy and 96.63 percent F1-score. Future research should suggest the employment of deep learning networks in all phases of palmprint authentication technology, starting from extracting the ROI to matching. We discovered that not all deep learning models need a huge number of images that can provide meaningful results.

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