Siamese Network-Based Palm Print Recognition

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Abstract—palm print recognition is a biometric technology used to identify individuals based on their unique comfort patterns. Identifying patterns in computer vision is a challenging and interesting problem. It is an effective and reliable method for authentication and access control. In recent years, deep learning approaches have been used for handprint recognition with very good results. We suggest in this paper, a Siamese network-based approach for handprint recognition. The proposed approach consists of two convolutional neural networks (CNNs) that share weights and are trained to extract features from images of handprints, which are then compared using a loss of variance function to determine whether the two images belong to the same person or not. Among the 13,982 input images, 20% are used for testing, 80% for training, and then passing each image over one of two matching subnets (CNN) that transmit weights and parameters. So that, the extracted features become clearer and more prominent. This approach has been tested and implemented using the CASIA PalmprintV1 5502 palm print database, the CASIA Multi-Spectral PalmprintV1 7,200 palm print, and the THUPALMLAB database of 1,280 palm print using MATLAB 2022a. For 13,982 palmprint recognitions in the database, the equal error rate was 0.044, and the accuracy was 95.6% (CASIA palmprintV1, THUPALMLAB, and CASIA Multi-Spectral palmprintV1). The performance of the real-time detecting system is stable and fast enough. The Siamese network approach is particularly useful in cases where there are large numbers of classes with a small number of observations for each, and the network does not need to be retrained when adding or updating data. Overall, the results show that the proposed Siamese network can work with different databases and with unbalanced data, and can provide very good results. Future work can explore the application of this approach to other biometric recognition systems, and investigate the potential of combining it with other deep learning techniques to further improve accuracy and performance. Compared to previous research, the proposed Siamese network achieves very high results with the use of a large and compact database and three different databases. The approach provides a reliable and stable real-time detecting system.

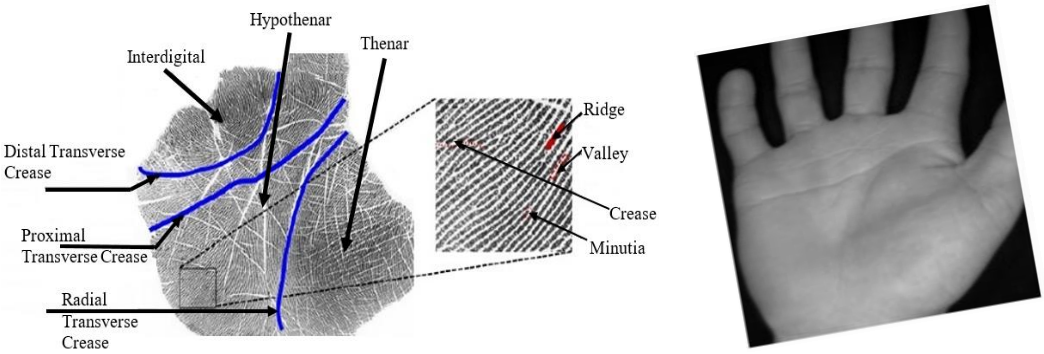
Keywords—Convolution Neural Network (CNN), Palmprint Recognition, Siamese Neural Net (SNN)

1. INTRODUCTION

A palm print refers to an image obtained from the palm region. It can be an online photo with a scanner or CCD or an offline photo where the photo is taken with paper and ink. The palm consists of major lines, minor lines, and cutaneous edges. It differs from a fingerprint in that it also contains other information such as texture, marks, and indents that can be used when comparing one palm to another [1]. By its nature, palm print recognition applies many of the same distinguishing characteristics that have allowed fingerprint recognition to be one of the best-known and most widespread biometrics. To understand this concept of recognition, one must first understand the physiology of the ridges and valleys of a handprint. Upon registration, the palm print appears as a series of dark lines representing the raised portion and peak of the skin undulating by friction, while the valley between these bumps appears as a white area and is low. The palm print is enduring and unique, it has been used for more than a century as a reliable form of identification [2]. Due to its non-absorption and safe use, this scientific technology has been applied in the fields of computers, gates, and security at airports. The comfort of the hand contains a group of major lines, wrinkles (secondary lines), and leather edges [3]. As compared to fingerprints, the palm contains more distances, signs, and textures that contribute to the feeling of comfort [2, 4]. Palm imprint can be either an online image (for example, a scanner or captured by a CCD) or ink and paper any image that is not connected to the Internet [2, 5].

There are many difficulties and problems in palm print recognition technology, deformation of the skin; hand has several joints, and computational complexity. The major aim of this research is to investigate and evaluate the processes of the palmprint identification system using one of the more specialized algorithms of deep learning techniques. A new method will be proposed and applied to different palmprint images to enable the assessment of their suitability and limitation when used in real applications. Palmprints pose certain advantages over fingerprints, such as the provision of additional features like wrinkles and principal lines, which can be easily extracted from images of slightly lower resolution. Palmprints provide more information than fingerprints; hence, palmprints can be used to make an even more accurate biometric system. The research considers a deep learning methodology.

The paper employs three datasets, the first of which is Casia Palmprintv1, which was collected from 312 persons, and the photo collection consists of 5502 images. People are required to collect the right and right hand. The self-developed palm print recognition device by wiping all the images with a gray level of 8 -bit and with JPEG format. Figure 1 shows palm print image from CASIA Palmprintv1 and the details of palmprint [6]. The second database consists of 7200 taken of 100 people taken by multi-spectrum photographs. Two sessions are taken on the palm of each hand. In each three-sample session, more than a month separated, JPEG files are used in all gray-level -level handy pictures, (see Figure 2) [7].



(a) Details of palmprint. (b) Palm print from CASIA palmprintV1 [6].

Figure 1. Palm print from CASIA palmprintV1 [6].

THUPALMLAB, another palm print database, contains 1,280 photos of the palm print. Figure 3 shows a palm print from THUPALMLAB. They took it using an 80-person HISIGN handmade hand scanner (2 hands, each with 8 imprints). The photos are all 20400×2040 pixels with a resolution of 500 points per inch [2, 8].

Figure 2. Palm print from CASIA Multispectral-PalmprintV1 [7].

Basic neural networks are learning-oriented information processing systems. A Siamese network was used in this paper because it is a type of deep learning architecture that is used to compare two inputs and determine whether they are similar or not. The Siamese network works by first extracting features from each image using convolutional neural networks (CNNs). It has been used in many applications, including palm print recognition. The Siamese network works by taking two pictures of a palm print and comparing them to see if they match. These features are then compared using a distance scale such as Euclidean distance or cosine similarity. The distance between the two trait vectors is then used to calculate a similarity score, which can be used to determine whether or not the prints are from the same person. The Siamese network has proven effective in recognizing palm prints with high accuracy. This makes it an ideal tool for biometric authentication systems, as it can quickly and accurately check if someone is who they are [9].

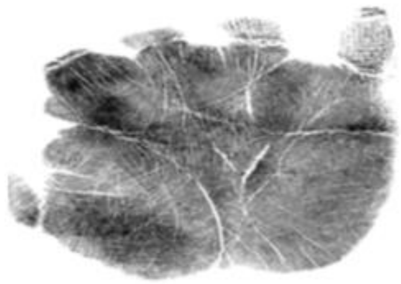


Figure 3. Palm print THUPALMLAB [8].

2. RELATED WORKS

Over the past years, many research papers have been published on palm print recognition. Fatima and Ebtesam developed a method using VGG16 with many filters in 3x3 kernel size. The VGG16 network topology is very unique so it is subject to change and development and is adaptable to different datasets. The total number of images utilized in this study is 13,982, with 20% used for testing and 80% for training. It categorized the images using the SoftMax function after passing through convolution layers and then the max-pooling layer to become more prominent and clearer to the extracted properties. The CASIA Multi-Spectral PalmprintV1 Database has 7200 palm prints, CASIA PalmprintV1 Database contains 5502 palm prints, and the THUPALMLAB database contains 1280 palm prints. The rating accuracy percentage for this approach is high, reaching 97.32% from 13982 images. The rate of equal error was 0.0268 [2]. Dai et al. proposed a new high-precision palmprint recognition algorithm. It includes the use of multiple features, namely fine detail, density, orientation, and key fonts, for great palmprint recognition. The matching performance of the traditional algorithm is improved. They used a new fusion system for a specific application that works better than traditional fusion methods, and they used the Niemann-Pearson rule of thumb. Experimental results in a database of 14,576 full palm palmprints show that the algorithm works well. The print recognition rate is from 82.0 to 91.7 percent. One of the reasons for using this method is high-security applications (e.g., forensic use) from which more useful information can be extracted [10]. Zhang et al. proposed a 3D palmprint recognition method by exploiting the 3D structural information of the palm surface. Structured optical imaging is used to acquire 3D handprint data, from which several types of unique features are extracted, including mean curvature image, Gaussian curvature image, and surface type. They used the established 3D palmprint database, The results showed that 3D palmprint technology has a high recognition performance. Although 2D palmprint recognition can achieve high accuracy, 2D palmprint images can be easily falsified and a lot of information is lost, but the palmprint recognition The three-dimensional hand has a higher anti-counterfeiting ability and is more robust in the face of light differences and serious scratching of the palm surface. Meanwhile, by integrating 2D and 3D palmprint information, a much higher discrimination rate can be achieved [11]. Zhao et al. proposed a deep discriminant feature extraction system (Deep Convolutional Networks (DDR) which is flexible and practical as this system produces the best performance for fingerprint recognition. In general, DDR achieved high performance on multispectral PolyU databases with M_R, M_B, M_G, and M_NIR. They used IITD and CASIA databases. Through learning deep discriminative convolutional networks (DCNN) called deep discriminant representation (DDR), DDCNs trained with limited training data are learned to extract deep discriminative features that contain global and local embedded features abstracted from a handprint. The results were based on IITD (EER-0.021%, ARR-98.70%) and CASIA (EER-0.005%, ARR99.5%) databases [12]. Zhang et al. developed a method using a multi-task learning approach, which simultaneously learns representations for both palmprint recognition and palmprint segmentation. The system was trained on a dataset of over 50,000 palm images and achieved an accuracy of 99.1% on a test set [13]. Table 1 summarizes the work related to palmprints [2].

Table 1. Summary of related works [2].

Reference	Dataset	Dataset Size	Methodology	Performance
X. Y. et al. (2021)	FVC2002	800	Multi-resolution Attention Network (MAN)	93.5%
A.A.et al. (2021)	PolyU	2,048	Attention-based Multi-task Network (AMN)	94.3%
X. L. et al. (2020)	PolyU	2,048	Multi-task Learning-based Deep Convolutional Neural Network (MTL-DCNN)	93.9%
R. T. et al. (2020)	CASIA Palmprint V1	10,800	Multi-scale Network (MS-Net)	94.2%
M. K. et al. (2019)	PolyU	2,048	Multi-Scale Convolutional Neural Network (MSCNN)	89.58%.
Anjali D. et al. (2019)	PolyU	2,048	Deep convolutional neural network	94.44%.
M. Raza et al. (2018)	FVC2004	1,232	A combination of CNN and Long Short-Term Memory (LSTM)	93.75%
R. S. S. et al. (2018)	FVC2002	800	Multi-resolution CNN	92.5%
Proposed system	CASIA-PalmprintV1 and CASIA-Multi-Spectral-PalmprintV1 and THUPALMLAB	13,982	Siamese network(SNN)	95.6%

3. PROPOSED SYSTEM

Figure 4 depicts the proposed system's structure. This paper describes the general idea of the proposed system and its sub-problems. Siamese nets are effective methods for palm print recognition systems because they include convolutional neural networks (CNN), which achieve sophisticated performance for tasks such as image recognition, image segmentation, and language modeling. But using convolutional neural networks (CNN) as the main network without Siamese makes one problem is that it requires a lot of tagged data. Sometimes not a lot of data is available for a particular task. Fewer data means that the deep learning model will not be able to properly model the different classes and will perform poorly. This is where Siamese nets come to the rescue. It helps to build models with good accuracy even with fewer samples per class and an unbalanced distribution of the class. Siamese net (SNN) They are especially useful in cases where there are only a few notes for a large number of categories. In some conditions, there is insufficient data to train a DCNN to categorize images into these categories. Where the Siamese network can tell whether two imagesiare from the sameiclass.

3.1 Training Phase

The sample data is separated into training and test data at the start of the task. The training technique is being carried out by a small group of 80 people. Each set of training data is separated into tiny batches, and training errors for each small batch are determined. The suggested neural network has twin subnetworks, which have the same setup, parameters, and weights. We merely train one of the two subnets and utilize the identical settings for the other. The test set will be used to assess final competency when the training method is completed.

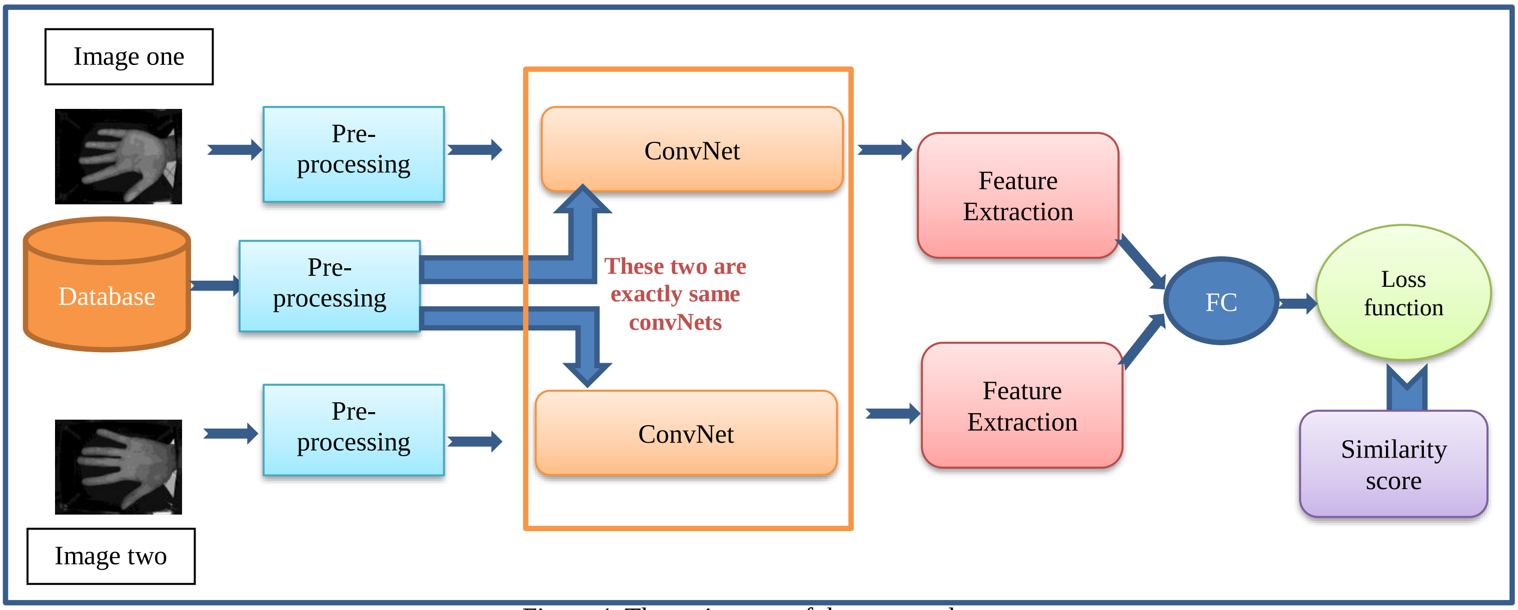


Figure 4: The main steps of the proposed system.

Algorithm 1: Implementation the major steps of the proposed Siamese network model.

```
% Define the Siamese network architecture
inputSize = [120 120 1];
lgraph = siameseNetwork(baseNetwork, 'InputSize', inputSize,
'NumClasses', numClasses);

% Define the training options
options = trainingOptions('adam', ...
    numIterations = 2500;
miniBatchSize = 250 ;
learningRate = 6e-5;
gradDecay = 0.9;
gradDecaySq = 0.99;
executionEnvironment = "auto");
% Load the palm print dataset and split into training and
validation sets
imds = imageDatastore('palmprint_dataset', ...
    'IncludeSubfolders', true, ...
    'LabelSource', 'foldernames');
[imdsTrain, imdstest] = splitEachLabel(imds, 0.8);

% Train the Siamese network
net = trainSiameseNetwork(imdsTrain, lgraph, options);

% Evaluate the trained network on the test set
YPred = classify(net, imdstest);
Ytest = imdstest.Labels;
accuracy = mean(YPred == Ytest);
fprintf("test accuracy: %f\n", accuracy);
```

3.2 Preprocessing

The simple definition of data preprocessing is a data mining technique for converting raw data collected from different sources into cleaner information that is more business-friendly. In other words, an initial step takes all available information to organize, sort and combine it. Many factors affect the operation and accuracy of the system, and among these factors are contrast, lighting angle level, noise, palm clarity, and camera resolution. We need to optimize the images before they are introduced into the proposed system. We need several steps to configure the images and enter them into the system. In the proposed system, three different databases (unbalanced) were used, each database differs from the other in several matters, including the number of subjects, the number of photos in each subject, the devices that were used to capture these photos, the difference in lighting conditions, the accuracy, and the difference in several other things, which necessitated the use of a different pre-processing for each database to enhance prediction in the proposed system. Figure 5 and Figure 6 show the pre-processing stage for the two databases used.

Algorithm 2: Palm Print Siamese Neural Net (PPSNN) Image Pre-processing.

```
T-Input← PPSNN Images.
T-Output← Pre-processing Image
  Begin
##%For each image from the first database in the total database
 T-data1← T-Input
    C-data1← Converted( T-data1, grayscale image)
    R-data1← Resize(C-data1,120*120)

 % Edge detection and image enhancement by a Laplacian of Gaussian (LoG ) filter
   F← fspecial("log",[7 7],0.1)
   L-data1← Convolution (F, R-data1)
   MF←mean fliter
   M-data1← Convolution(MF, L-data1)
   S-data1← Subtract ( M-data1, T-data1)

 % Convolution of the step previous result and the mean filter
   M-data1← Convolution(MF, S-data1)
 %Image to binary conversion
  B-data1← Converted(M-data1, binary)

##% For each image in the second database
 T-data2← T-Input
 C-data2← Converted( T-data2, grayscale image)
  R-data2← Resize(C-data2,120*120)
% Lighten the image (increase the lighting) with adjustment
  I-data2← imadjust(R-data2)

% Add sharpness to the image using the Sharpen filter
 kernel = [-1 -1 -1; -1 9 -1; -1 -1 -1]
  SH-data2← Convolution (kernal, I-data2)
  % Smooth the image with the mean filter
   SH-data2← Convolution(MF, SH-data2)

##% For each image in the third database
T-data3← T-Input
 C-data3← Converted( T-data3, grayscale image)
  R-data3← Resize(C-3120*120)

##% Create one database from the three existing databases before entering the proposed system.
T-Output←( B-data1, SH-data2, R-data3)

End
```

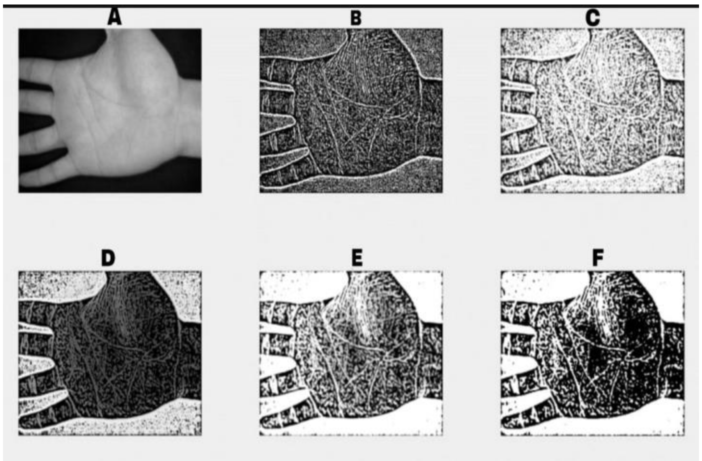


Figure 5: Result of CASIA-PalmprintV1 preprocessing stages. A: the original image, B: edge detection of the image using Laplacian of Gaussian, C: image convolution using the median filter, D subtraction of the image, E: image convolution using the mean filter, and F: the binary image.

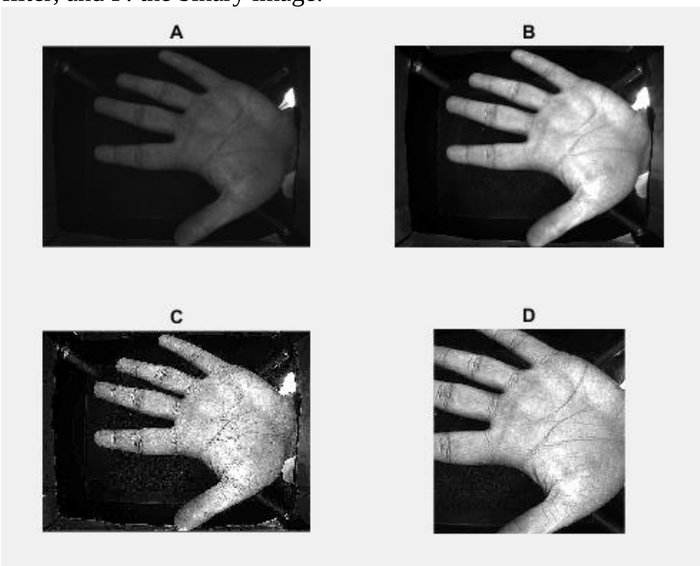


Figure 6: the result of CASIA-Multi-Spectral-PalmprintV1 preprocessing stages. A: the original image, B: adding lighting to the image, C: Sharpening the image, and D: Smoothing the image.

4. The SNN ARCHITECTURE

The SNN architecture uses two identical subnets for input processing. Subnets share weights, which means that the same weights are used for both networks. Then the output of each subnetwork is compared using a distance scale, the proposed model for each subnetwork needs the input image to be 120×120×1. While the middle layers make up the bulk of the proposed system. Four convolutional layers employ the Narrow Normal Distribution to initialize weights and biases, filters that vary in number and size from layer to layer, four rectified linear units (ReLU), and a maximum of three pooling layers (Stride=2×2). The last layer for each subnet is fully connected, with an output size of 4096 and weights and biases initialized using a narrow normal distribution. The two subnets were then united by a fully connected layer, which was expected. The suggested SNN layers are depicted in Figure 7.

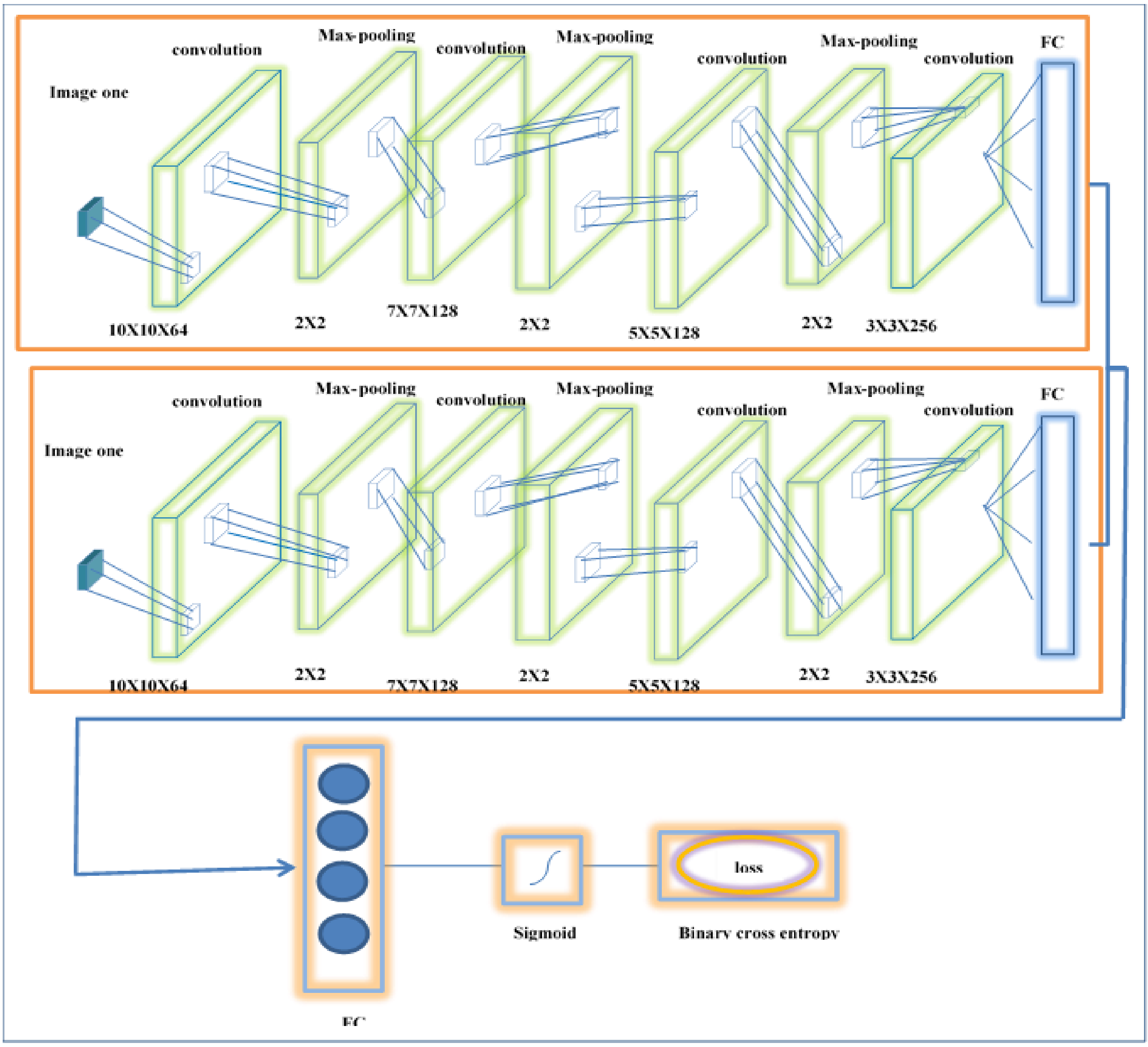


Figure 7: The proposed SNN layers.

5. RESULTS

Tuning the proposed SNN parameters for palm print discrimination is of great importance because it has an important and effective role in achieving the goal of the proposed system, which is high-accuracy discrimination. Moreover, these parameters directly affect the training speed and the memory space needed to store the variables used.

Hyperparameters include image size, activation functions, filter size, optimizers, learning rates, etc. To explore the effect of variation hyperparameters on the performance of the proposed SNN model, a reference SNN model was constructed by repeating several experiments. The effect of different hypervariable on the performance of the proposed model is investigated by changing different hyperparameters of the SNN reference model. Based on the results of the experiments, the proposed SNN model was built. The reference model consists of four convolutional layers for feature extraction and a fully connected layer for each subnet. The proposed system consists of two subnetworks with completely similar weights and parameters and a fully connected layer

5.1 Palm Print Image Size and Its Impact on Accuracy:

Image size is an important factor affecting SNN training and affects training speed and accuracy. Figure 7 shows the experimental results. Several image sizes (105×105), (110×110), (115×115), (120×120), (125×125), and (130×130) were examined, the best image size was (120×120), and it is determined according to the best results according to the resolution, and the lowest performance was the image size 105×105.

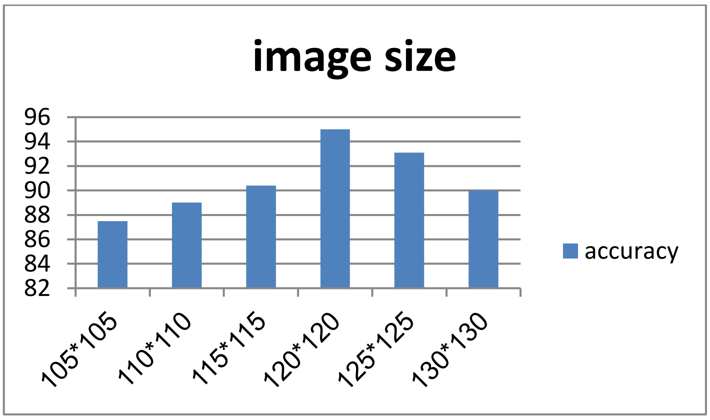


Figure 8: The relation between image size and accuracy.

5.2 Choosing a Suitable Learning Rate

In SNN training, the learning rate is an important parameter affecting error convergence and weight adjustment. A smaller learning rate can help the model converge with a good solution, but it can also slow down the training process. A higher learning rate can speed up training, but it can also cause the model to converge on a suboptimal solution or even diverge. Generally, starting with a relatively large learning rate is a good idea, and then reducing it as training progresses. This can help the model quickly identify key features of the data and then improve its predictions as it continues to train. Therefore, it is very important to select the appropriate learning rate to improve the efficiency of network training. In this experiment, different learning rates were used to train the SNN, and we obtained different validation accuracy and test accuracy, as shown in Figure 8. In this experiment, the learning rate of 0.00006 achieved the best performance, while 0.001 achieved the lowest performance.

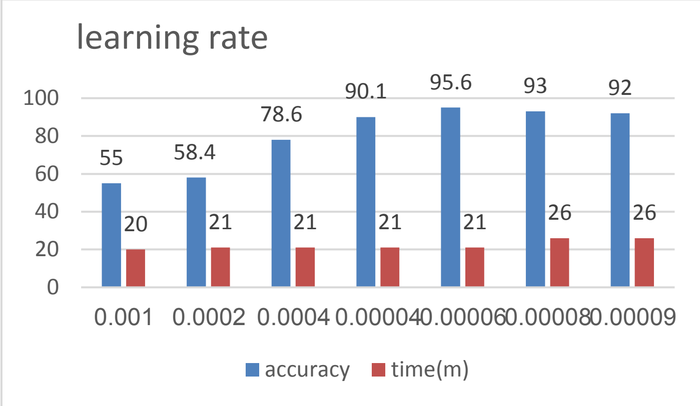


Figure 9: The relation between learning rates and accuracy.

5.3 Effect of Filter Size:

Filter size is also an important factor affecting SNN training and the time spent on training and accuracy. Table 2 shows the results of the experiment. In this paper, several filter sizes were examined for each convolution layer.

5.4 Choosing a Suitable Optimizer

As it is used to adjust neural network features such as weights and learning rates to decrease losses, optimization plays a significant role in boosting classification accuracy and model speed for various DL models and classification tasks. Therefore, several optimization algorithms were tested within experiments to find the best model, including Root Mean Square Propagation RMSProp, Steepest Gradient Descent, and Adam's optimization algorithm. The performance of the Adam optimizer was marked with the highest performance as shown in Figure 9, and RMSProp was the lowest performance during the trials. Therefore, the Adam algorithm was chosen as a training optimizer for the proposed model.

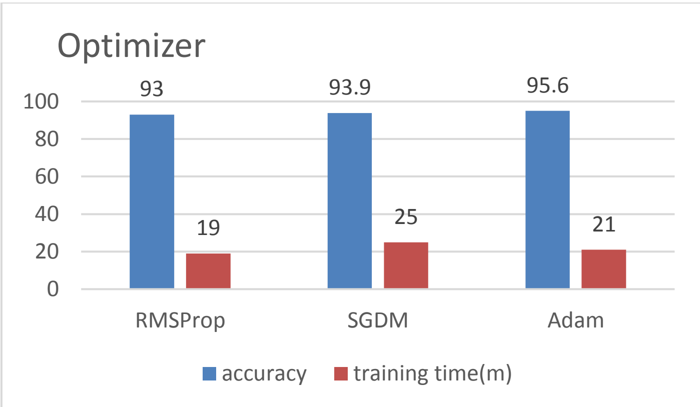


Figure 10: The relation between optimizer and accuracy.

Table 2: The experiment with filter size.

Id	One-Convolution Layer	Two-Convolution Layer	Three-Convolution Layer	Four-Convolution Layer	Test accuracy
1	11x11	9x9	7x7	5x5	89.7%
2	10x10	7x7	5x5	3x3	95.6%
3	5x5	5x5	5x5	5x5	88%
4	9x9	7x7	7x7	5x5	90%
5	10x10	9x9	7x7	5x5	92.9%

5.5 Choosing the SNN Model Structure

Four models of SNN were used to find out the effect of different model structures of SNN on performance accuracy, a model with the number of layers of each subnet on two convolutional layers, the second has three convolutional layers, and the third contains four convolutional layers, while the last model contains five convolutional layers. They trained in image size (120×120), improved by Adam, the learning rate is 0.00006, the Relu function is used in the Convolutional layer, and the mini-batch is 80. Figure 10 shows the results of applying different SNN models. Through experiments, the SNN model with four layers has the highest performance, with an accuracy of 95.6. On the other hand, the performance of the two-layer SNN model is the lowest. The loss and training accuracy curves for different SNN models with two-layer, three-layer, four-layer, and five-layer are shown in Figures 11, 12,13, and 14, respectively.

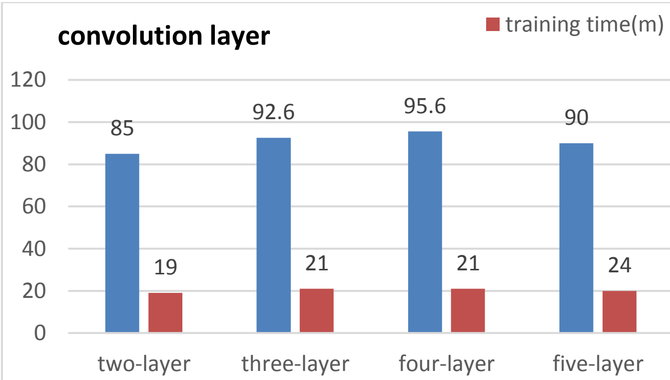


Figure 11: The relation between the number layer and accuracy testing.

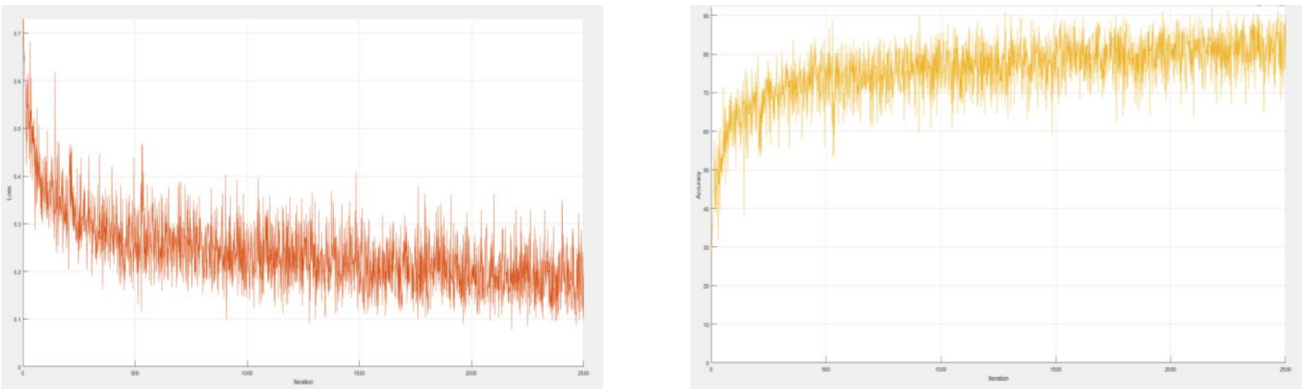


Figure 12: The Accuracy and the loss rate of two-layer. Left: the accuracy, and right: the loss.

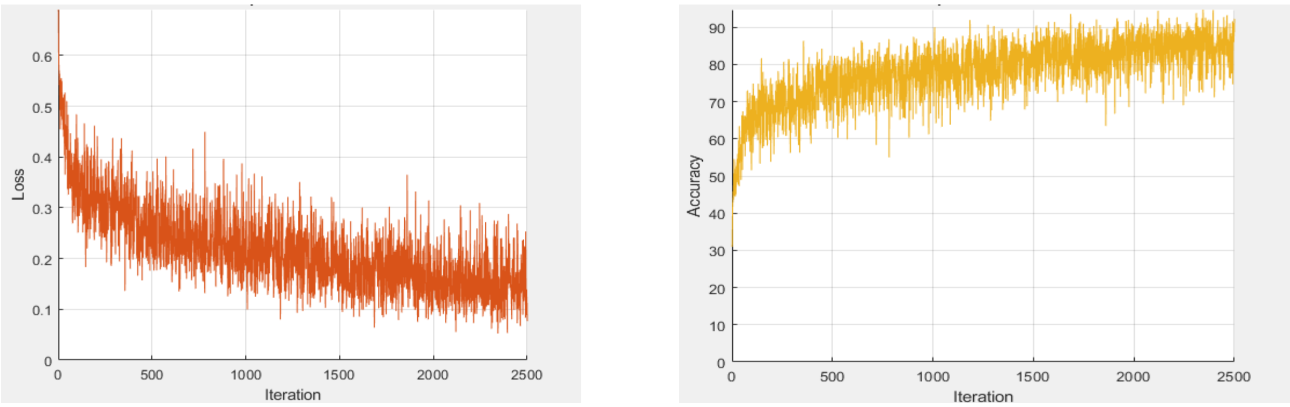


Figure 13: The Accuracy and the loss rate of three-layer. Left: the accuracy, and right: the loss.

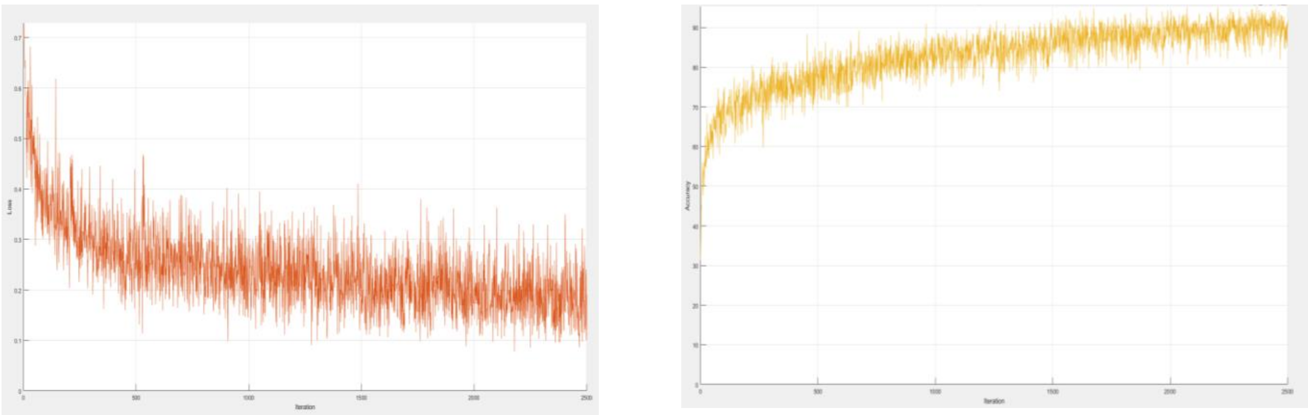


Figure 14: The Accuracy and the loss rate of the four-layer (proposed system). Left: the accuracy, and right: the loss.

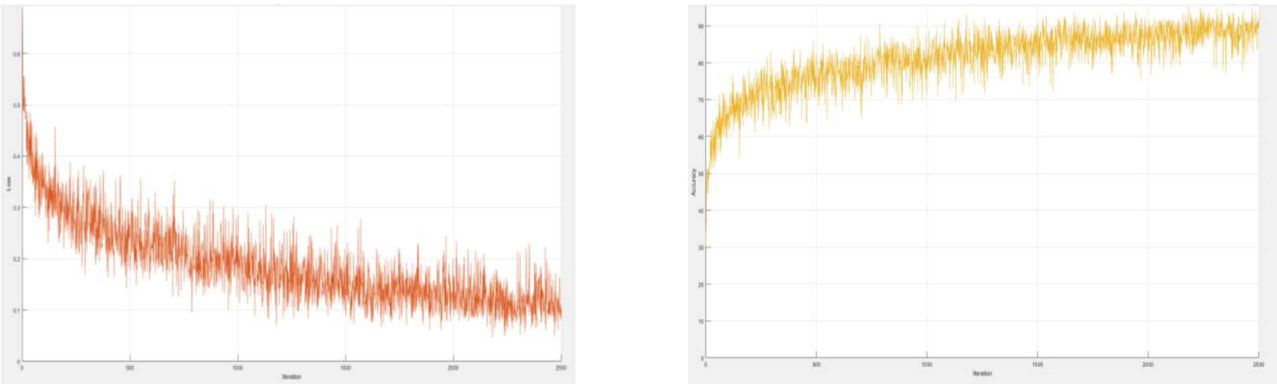


Figure 15: The Accuracy and the loss rate of the fife layer. Left: the accuracy, and right: the loss.

5.6. Evaluation Process

To calculate the accuracy of the network, create a set of five random mini-batches of test pairs to evaluate the network predictions and calculate the average accuracy over the mini-batches.as following:

*****Extract mini-batch of image pairs and pair labels
*Convert mini-batch of data to dlarray. Specify the dimension labels. "SSCB" (spatial, spatial, channel, batch) for image data.
*If using a GPU, then convert data to gpuArray.
*Evaluate predictions using trained network
*Convert predictions to binary 0 or 1
*Compute average accuracy for the minibatch
*Compute accuracy over all minibatches. The accuracy of the proposed system is 95.6%

6. CONCLUSION

Palm print recognition using the Siamese network is a promising technology that has shown great potential in accurately identifying individuals based on their palm prints. The Siamese network architecture allows for the comparison of two palm prints and generates a similarity score, which can be used to determine if the two prints belong to the same person or not. This technology has several advantages over traditional methods of palm print recognition, such as being less affected by changes in lighting and orientation. However, further research is needed to improve the accuracy and efficiency of this technology before it can be widely adopted in various applications such as security systems and access control. Overall, palm print recognition using the Siamese network is a promising area of research that has the potential to revolutionize the field of biometric identification. In this paper, several experiments were carried out on the proposed system using an unbalanced database and many classes. As the number of classes rises, so does the accuracy rate. Also, the proposed pre-processing procedure, which uses a mean filter to eliminate noise and reflection in the image and define the inner and outer bounds of the image using effective optimization, is significant and influences the accuracy of prediction and ratio calculation. The procedure is based on contrast enhancement. The proposed method is distinctive in terms of performance and data volume when compared with the results of several previous studies. In this study, we identified extremely diverse characteristics from palmprint databases, which were then integrated and utilized as a single base even though these images were acquired by devices at resolutions that differed from previous methods published in the works of literature in several touchless palmprint datasets. The proposed system ascertained that the accurateness results are very good in heterogeneous and imbalanced databases using local descriptor techniques, which may perform poorly in these databases. The proposed system scored a prediction accuracy of more than 95%.

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