Palm Print Identification of Individuals Based on the Residual Neural Network

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Abstract:

Palm print recognition technology is one of the most important biometric technologies and has received great attention in terms of scientific research and practical applications. In this article, the technology is based on the ResNet50 algorithm, also known as the Residual Neural Network, and the Convolutional Neural Network (CNN) framework for palm print recognition. First, based on the geometric features of the palm print, the region of interest (ROI) area for the palm print was sculpted. The post-processing ROI is then considered an input to the convolutional neural network. The network can adapt to different palmprints by developing training data. Intermediate Layer Activations for the palm print have also been visualizing and this is a distinct work of the article. The CNN-based palmprint recognition system has an overall accuracy of 98.55 percent, and the model parameters are substantially lower than the standard network model, according to the test findings. It outperforms the typical palmprint recognition method in terms of accuracy.

Keywords: palmprint, ResNet, convolution neural network, recognition, identification.

الملخص:

تعد تقنية التعرف على بصمة الكف من أهم تقنيات القياسات الحيوية وقد حظيت باهتمام كبير من حيث البحث العلمي والتطبيقات العملية. في هذه المقالة، اعتمدت هذه التقنية على خوارزم50 ResNet ، والمعروفة أيضًا باسم الشبكة العصبية المتبقية، وإطار عمل الشبكة العصبية الالتفافية (CNN) للتعرف على بصمة اليد. يتم أولاً، بناءً على السمات الهندسية لبصمة الكف، تم نحت منطقة ذات الاهتمام (ROI) لبصمة الكف. تعتبر المنطقة ذات الاهتمام بعد المعالجة مدخلاً للشبكة العصبية الالتفافية. ويمكن للشبكة التكيف مع بصمات الكف المختلفة من خلال تطوير بيانات التدريب. وتم أيضًا تصور عمليات تنشيط الطبقة المتوسطة لبصمة الكف حيث تبلغ دقة نظام التعرف على بصمة اليد المستندة إلى 98.5% CNN، ومعامل النموذج أقل بكثير من نموذج الشبكة القياسي، ووفقًا لنتائج الاختبار إنه يتفوق على طريقة التعرف على بصمة اليد النموذجية الاخرى من حيث الدقة.

الكلمات المفتاحية: بصمة الكف، ResNet، الشبكة العصبية الالتفافية، التعرف، التعريف.

1. Introduction

With modern technical progress and scientific development, confidentiality and security requirements for practical applications have become more and more important in terms of accuracy and security of identity authentication for individuals using biometric palmprints. Traditional identity authentication has drawbacks, including hacking, theft, and identity fraud. The technology of using biometrics helps a lot in solving these equations by distinguishing between the physiological and behavioral characteristics of people.

Palmprint recognition is a biometric palmprint recognition technology that has been proposed in recent years, such as facial recognition [1], palmprint recognition [2], palmprint recognition, and iris recognition [3], as well as identifying the vein. [4].

Our paper proposes a palmprint recognition algorithm based on a deep convolutional neural network (CNN) that learns palmprint characteristics from large amounts of data and exploits the network's capacity to automatically extract palmprint convolution features. In the meanwhile, text recognition can be done directly on the palmprint master map [1]. The results of the experiments suggest that the proposed strategy can significantly increase the test's accuracy. The effect of network recognition and other approaches utilized in this paper are initially introduced in this paper. Then we prepare the data needed for the method, create the network, and tweak the network's parameters based on the data's training so that they may extract distinct features [2]. With the new palmprint, the trained features will be predicted. In addition, we normalize the data to increase the algorithm's accuracy; normalization can improve, and it may also improve the calculation's correctness. Finally, the tests show that the algorithm is capable of producing good results. The system mines all of the information in the palmprint image and does not require any artificially specified feature extraction processes, making the palmprint recognition algorithm much easier to understand.

2. Related Work

A convolutional neural network (CNN) is demonstrating its capabilities as deep learning progresses. It is frequently employed in a variety of domains, including pictures, phonetics, and natural language processing. The network does not need to rely on artificially defined features because it can extract features autonomously. Given the current trend, we want to achieve the best possible accuracy with deeper and more complicated networks, but this sort of network has downsides in terms of model size and running speed. There are two types of compact pre-training models and live training of tiny networks while building a small and efficient neural network, the major reason being to optimize the delay and consider the size of the model.

Several recent studies have used deep learning algorithms to study biometrics such as palmprint recognition. [3] proposes a unique strategy based on MPELM to increase the performance of the multispectral palmprint recognition method. To begin, the David Zhang approach is used to preprocess all palmprint images. Then, to fuse the multispectral palmprint images, apply an image fusion approach based on the rapid digital shearlet transform. Finally, calculate the final multispectral palmprint classification using the proposed MPELM classifier. The proposed model has an average accuracy of 97.33 percent, according to the testing results. [4] proposes a novel Gabor-based kernel principal component analysis (PCA) technique for palmprint recognition that integrates the Gabor wavelet representation of palm images and the kernel PCA method. The proposal's recognition accuracy was as high as 95.17 percent, according to the findings. A palmprint recognition system based on a scanner is presented in [5.] The palmprint images are captured and aligned automatically so that they may be processed further. Fisher discriminant analysis (FDA) and independent component analysis are two linear subspace projection techniques that have been tried and contrasted (ICA). The proposal's recognition accuracy was up to 95.2 percent and 95.7 percent, respectively, according to the findings. X. Xu and Z. Guo offer a method for modelling multispectral palmprint images as quaternions and extracting features using quaternion principal components analysis (QPCA) [6]. Multispectral palmprint images are analyzed using QPCA to extract features. The Euclidean distance is used to determine how different two palmprint images are. Given 3000 testing samples from 500 palms, the best GAR is 98.13 percent, according to the trial. In [7], proposes a unique contactless Palmprint identification system based on palm print principle line-based feature extraction [8]. The distances between endpoints and points of interception were determined and translated into frequency domain using the Discrete Fourier Transformed (DFT) approach. The suggested model was trained and found to be 98.55 percent accurate. [9] proposes a discrete wavelet transform-based technique for doing so. The findings showed that the proposal's recognition accuracy was up to 98 percent. The results reveal that the convolution neural network has been successfully applied in palmprint recognition. Palmprint recognition has yet to be applied to the ResNet-based model. A novel CNN model for palm print recognition is presented in this paper.

3. Palmprint Recognition Method

Discriminative pattern features may be automatically learnt from a large quantity of data using a convolution neural network (CNN), one of the most effective deep learning models used in the field of image recognition. It can create the effect of human eye recognition when the amount of data used is quite significant. As a result, we use it to recognise palmprints and get a high recognition rate by modifying the network layout. Figure 1 depicts the network structure.

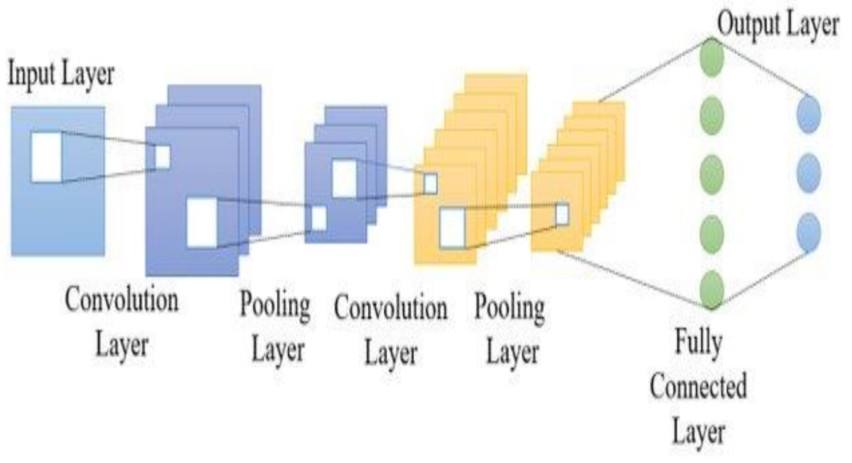

Figure. 1 General structure of a CNN

General structure of a CNN architecture which is based on several concepts as presented in figure.2. below.

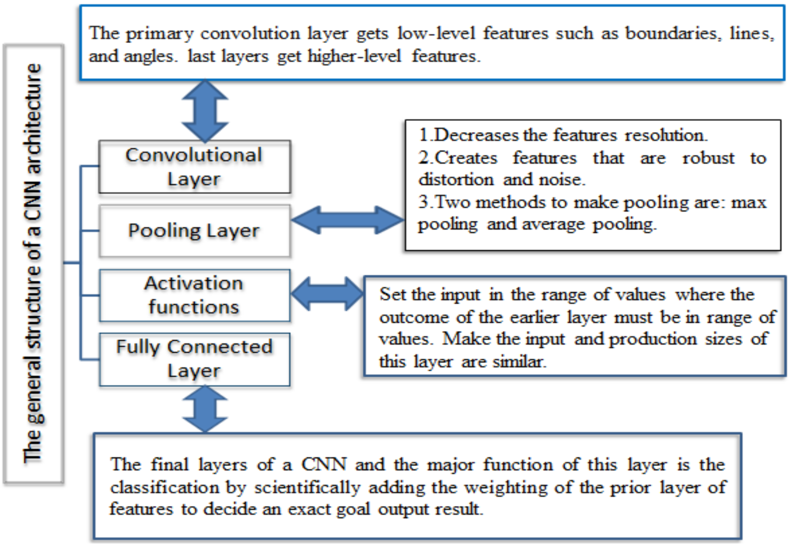

Figure.2. General structure of a CNN architecture.

3.1 Data Preparation

The 11k Hands dataset was employed in this study, which consists of 11,076 manual pictures (1,600 x 1,200 pixels) from 190 people ranging in age from 18 to 75, male and female, who were all requested to open and close their left and right fingers. This data is separated into two parts: the dorsal side of the hand and the palmar side of the hand, and working on the palmar side of this paper exclusively. Dorsal and palmar hands are presented with a uniform white background and nearly the same distance from the camera. There were 5,396 palmer images in total, comprising 2813 with the right hand and 2583 with the left, as shown in figure 3, which were separated into training and testing, with 4856 images used for training and 540 images used for testing. The test images are selected at random from the data. In the experimental stage, some distortion was included to reduce over-fitting in the training step. Meanwhile, the precision of the computation can be enhanced in order to boost the speed of the solution. The mean variance of the data was normalized during the experimental stage. The test data set cannot be simply normalized using the method; instead, the mean and variance of the training data set must be used to normalize the test data set.

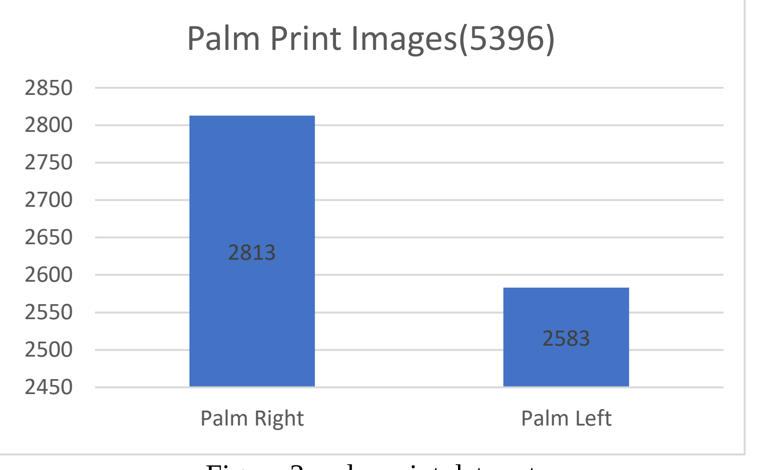

Figure 3. palm print data set

3.2 System Framework

Figure 4 shows the technological architecture of the proposed biometric system, which is based on the fusion of palmprint features at the matching score level. Our approach incorporates image pre-processing and deep-CNN based feature extraction in both stages (enrolment and identification). The extracted feature vector must be kept in the system database for the enrollment phase, while this feature vector must be subjected to a matching procedure for the identification phase to determine whether to accept or reject this individual at the decision step. It's worth noting that a normalization method is used before integrating the results from the unimodal systems. This improved technique utilizes each biometric modality and may be used to a unimodal biometric system.

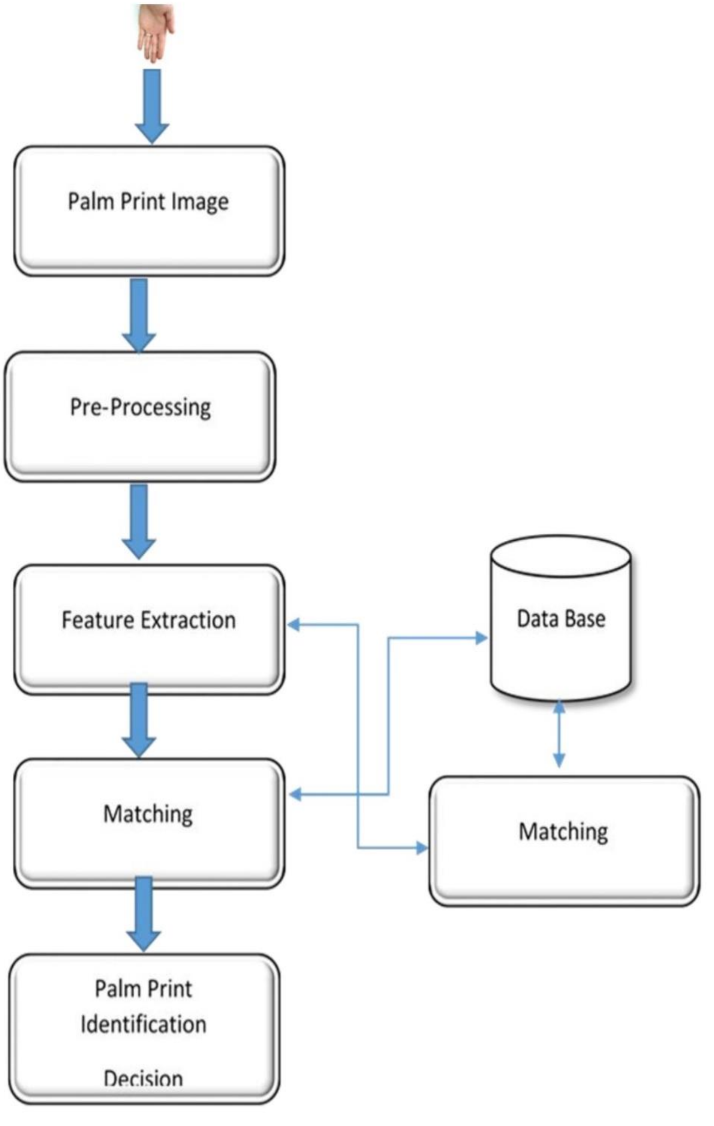

Figure 4. System Framework

3.3.1. Image preprocessing

The lines, wrinkles, triangles, and detail points in palmprint have a rich texture and structural qualities. Individuals have their own set of characteristics. Images produced from the same palmprints gathered at various periods will have varying degrees of rotation and translation, and the size of the palmprints collected at the same time may also differ. As a result, before extracting the feature and recognizing the palmprint, the effective return on investment area of the palmprint that comprises the major characteristics must first be extracted. Figure 5 depicts the full therapy procedure. Extraction of the return on investment is a major stage, as it leads to image alignment, increased feature matching efficiency, and, ultimately, a beneficial influence on recognition outcomes.

In a biometric identification system, defining a palmprint area of interest (ROI) is a crucial step. We utilized the same algorithm that was used in [9] for this. It entails establishing a coordinate system that allows the center region of the palm to be defined. The coordinate system is determined by using the gaps between the fingers as reference points. As a consequence, the H x W rectangle investment has a sub-image that is retrieved afterwards.

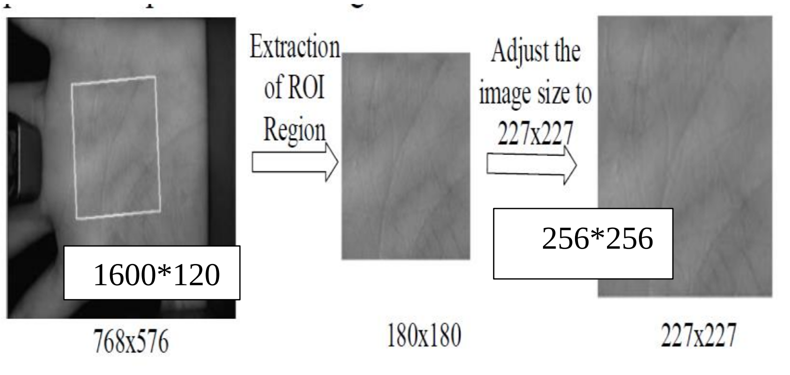

Figure 5. Palmprint image Preprocessing

3.3.2 Feature Extraction and Classification

The Convolutional Neural Network (CNN) [8] uses numerous banks of convolution filters to scan an input picture. To extract higher level feature vectors, it may be run with many layers and filters. CNN stands for "convolutional neural network," which is a type of deep neural network used in pattern recognition and image processing. The CNN algorithm is a multilayer perceptron that is specifically developed to analyze two-dimensional signal information such as images. The CNN architecture (see Fig. 2) is made up of three layers which are convolutional layers, pooling layers, and fully-connected layers. As a result, the input image is convolved with some filters in the convolutional layer. This work can be completed in a number of ways. The outputs of this layer are decreased by utilizing the max-pooling function after each convolutional layer in order to minimize the size of the acquired feature, which is the duty of the pooling layer. Finally, the feature vectors of the input picture are produced in the output layer and utilized as Dense inputs for classification (matching).

3.3.3 Scores Normalization and Fusion Schemes

Each measured score may be translated into a common interval using the normalization procedure that is often employed in multimodal systems (data fusion). Min-Max is the most often used normalization approach in biometric identification systems. When the limitations (minimum and maximum values) of the scores given by the systems are known, this approach is more applicable. In this scenario, we can easily convert the scores vector's lowest and maximum values to 0 and 1, respectively. The score normalized using the Min-Max approach is given by the following formula:

$$\hat{v}_d = \frac{v_d - \min(v_d)}{\max(v_d) - min(v_d)} \qquad (1)$$

where Vd holds all of the scores computed between the test and all of the stored feature vectors, and the vector contains the normalized values.

The system's choice is based on the system designer's given system security threshold (To) and the calculated matching score (di 0). (depending on the desired security level).

The system makes the following choice for each user:

$$Decision \equiv \begin{cases} Accepted\ \ if & d_0^i \geq T_0 \\ Accepted\ \ if & d_0^i < T_0 \end{cases} \qquad (2)$$

Where di 0 is the estimated score for the ith individual and To is the security threshold for the system.

4. Experimental Results and Discussion

The precision of a biometric system is important. Depending on the technology, biometric parameters are utilized to determine the degree of accuracy. A collection of multispectral palmprint images obtained with a capture device produced by the 11k data set Gender recognition and biometric identification utilizing a large dataset of hand images is used in the assessment phase. A convolutional neural network may be adjusted using a variety of parameters. We need to determine the important characteristics that properly reflect our system in order to acquire the optimal CNN architecture and a high accuracy identification rate. There are hyper-parameters and extra parameters in any CNN architecture. The number of layers, the activation function, the learning rate, the batch size, the number of epochs, and the L2 regularization are all essential hyper-parameters. The filters size, number of filters, padding, stride, and pooling-layer, on the other hand, are the most essential extra factors. Our study concentrated on a few factors that we believe are important in our work, as well as the fact that other parameters adopted by default have delivered decent results, in order to create an effective biometric system with less complexity. Starting with a simple model and attempting to enhance it at each stage is a smart approach.

4.1 Visualizing Intermediate Layer Activations:

Understanding how the used deep CNN model can identify the input image necessitates looking at the output of its intermediate layers to observe how this research model views the input image. Similarly, by doing so, all researchers will have a better understanding of how these layers function.

For example, when given an image of a palm print from the input set, the outputs of numerous intermediate convolutions are linked to their respective activation layers of the trained Inception model, as shown in figure. 8.The original DHVs, as well as the intermediate activation layers, are shown in Figures 6 and 7. Figure 6 displays the original image, while Figure 7 shows the activation layers.

Figure 6. Original palm print image

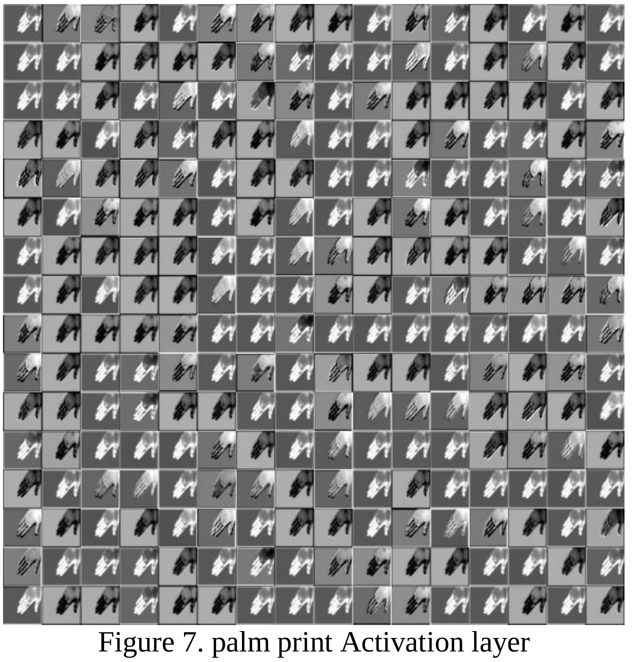
Figure 7. palm print Activation layer

4.2 Results

We utilized 4856 palmprint grayscale images as training data and 540 palmprint grayscale images as test data in the experiment. The accurate recognition rates achieved after numerous rounds of training were 98.55 percent. Because palmprints are such common characteristics, the resolution may be degraded, resulting in recognition problems. Table 1 shows comparisons with different approaches.

Table 1 comparison with other methods

Methods	Recognition Rate
PCA + GWR	95.17%
QPCA	98.13%
MPELM	97.33%
FDA	95.20%
ICA	95.70%
DFT	95.48%
DWT	98.00%
ResNet	98.55%

We can observe that our approach outperforms the majority of the conventional techniques in Table 1. Resolution and noise may readily sabotage this method. Our approach is a feature learnt from a vast quantity of palmprint data and does not require any preprocessing or feature extraction. As a result, it can adapt to a large amount of data while maintaining excellent accuracy.

We also look into the link between experimental results and the amount of training data. For varied training data sizes, Figure 8 demonstrates the link between the accuracy of our model network and the number of iterations throughout the training process. The accuracy rate of the verification set under various amounts of iterations volumes climbs initially and then stabilizes as the number of iterations increases.

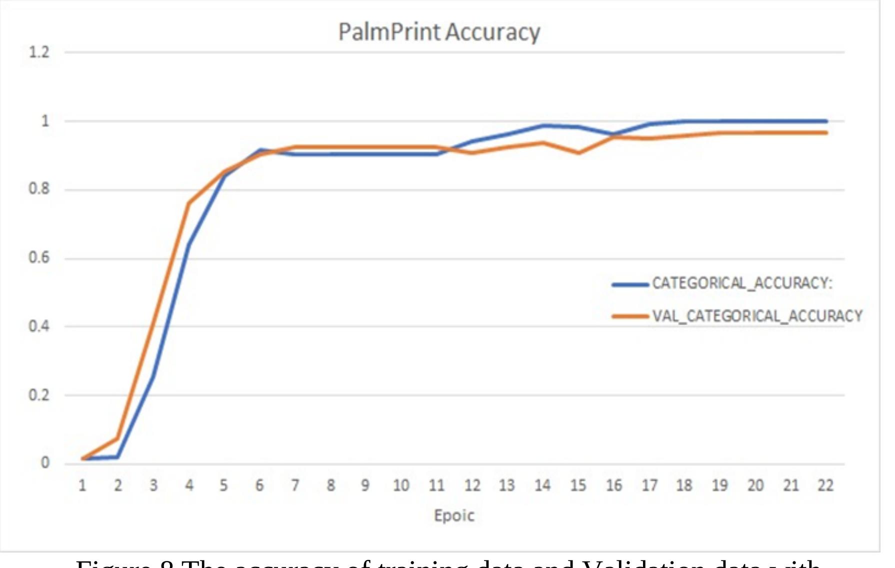

Figure 8 The accuracy of training data and Validation data with different amounts of iterations

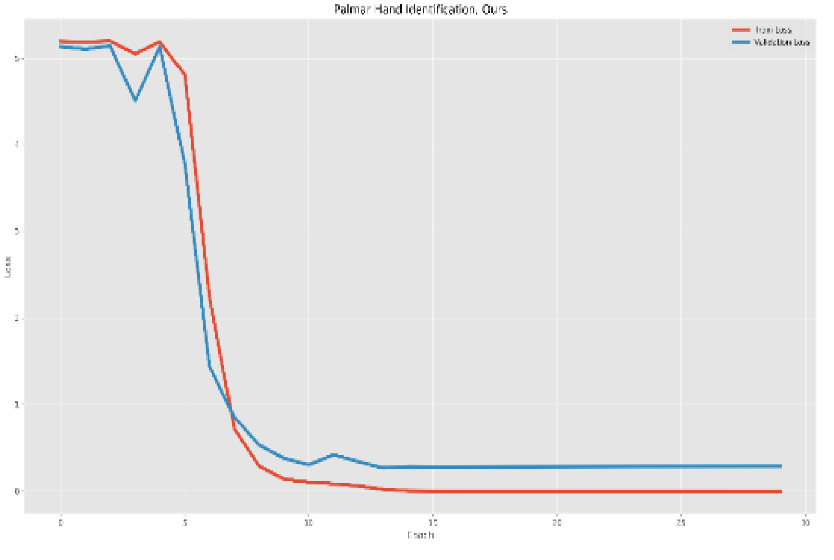

Figure 9 The Loss of training data and test data with different amounts of iterations

5. **Conclusion**

The ResNet50 algorithm, based on convolutional neural networks, was used to identify persons using palm print features in this article (CNN). The network can manage and adapt to diverse palm print variety by creating the training data based on the features of an individual's palm print and distinguishing it from other persons. The palm print feature may be recovered from the original handprint without image pre-processing or other special extraction using an efficient network architecture and training data, resulting in successful identification. The results of the experiments demonstrated that the technology is successful and trustworthy in recognizing palmprints with increased accuracy, and that it can be utilized in a variety of industries to assure high security and secrecy for institutions, companies, and others.

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