International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(RESEARCH ARTICLE)

AI-Driven Palm Print Authentication: A comprehensive Analysis of Deep Learning Approaches for Efficient Biometrics

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International Journal of Science and Research Archive, 2022, 06(01), 318–327

Publication history: Received on 25 May 2022; revised on 26 June 2022; accepted on 29 June 2022

Article DOI: https://doi.org/10.30574/ijsra.2022.6.1.0158

Abstract

Palmprint recognition is a kind of biometric identification that confirms a person's identity by analyzing certain discriminative characteristics found on their palm. The benefits of contactlessness, stability, and security have made it a popular choice. This is why a palmprint is a reliable biometric for human identification due to its unique characteristics. The area of people recognition is only one of several that has benefited from the proliferation of better computer techniques and uses of artificial intelligence (AI). In this research, we survey the state-of-the-art in image processing as it pertains to palm print identification and authenticity, and compare and contrast several approaches. This work focuses on a palm print feature that has garnered a lot of interest in the literature recently in this study. This work developed a deep learning model focusing on the palm print verification challenge. Not only that, but the study details the steps taken by biometric authentication systems, including preprocessing, feature enhancement, feature extraction, the classification process of palm print pattern recognition systems, and a number of experimental results pertaining to palm print pattern recognition methods. The CNN model outperforms competing algorithms in palm print recognition, with an accuracy of 98.5%. Various algorithmic and palm print identification approaches have been developed and successfully implemented in continuous evaluation. In this study, examine all of the strategies and formulate a superior one based on this survey. Each method requires different previous information. Additionally, a new method for contactless palm print identification and authentication was suggested in this study.

Keywords: Biometric Authentication; Palm Print Recognition; Artificial Intelligence (AI); Deep Learning; CNN.

1. Introduction

The security of information systems has become an increasingly important societal concern due to the rapid advancement of networks and information technologies. A key strategy to strengthen the reliability and safety of computer networks is biometric identification technology, which has grown in importance over the years. A kind of automated identification known as biometrics makes use of characteristics derived from human biology or behaviour. Unique personal qualities with stability, variety, and individual variances are biometrics. Fingerprints, faces, iris scans, signatures, finger veins, and other biometrics have all been used. At the same time, technology for palmprint recognition is advancing at a fast pace [1][2]. Many sectors are considering biometric recognition technologies, including those dealing with speaker identification, palm print recognition, iris print surveillance, and finger texture (FT) verification[3].

The palmprint is one of the most distinctive and useful biological traits, and it differs from person to person. The characteristics of the palm's texture and lines, which make up a palmprint, remain constant over time. Because of its bigger surface area, collected palmprints provide more personal information than fingerprints. Thus, palmprint is becoming more popular among researchers because of its many benefits[4].

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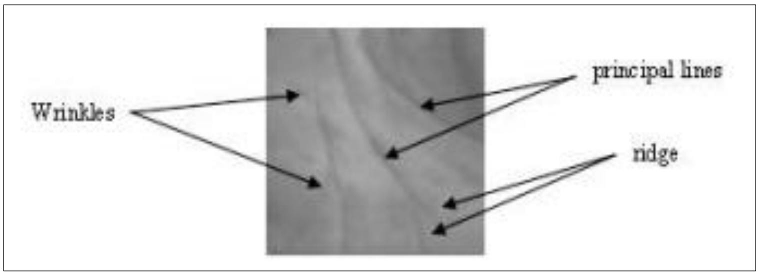

Figure 1 A palm print image and its textures of principal lines, wrinkles and ridges[3].

Because of its extensive characteristics, the palm print characteristic is one of the most intriguing physiological biometrics. Its typical location is on the palm side of the hand, midway between the digits. The surface exhibits a variety of textures, including major lines, wrinkles, and ridges[5], as seen in Figure 1. These textures are readily recognisable. Between the third and fifth months of pregnancy is when palm prints develop, and once the baby is born, these superficial lines show [6]. It is possible to capture an image of a palm print using a cheap, low-resolution camera or scanner. The three aforementioned texture types—principal lines, wrinkles, and ridges—make up the palm print. They may get a different kind of structure from each of these textures. Overall palm print structures provide a strong foundation for person verification.

Because each person's fingerprint is distinct and immutable, palmprint recognition systems have great promise for dependable personal verification and identification. Therefore, palmprint recognition might be a very accurate and dependable method of biometric authentication. Because of its self-positioning capabilities and simplicity of use, palmprint recognition has earned a reputation as a non-invasive biometric technology. Forensic and civilian biometrics based on palmprints are therefore quite versatile[7]. Traditionally, researchers combine ML methods, like SVM[8], KNN [9], etc., with feature extraction methods, like LBP [10] and HOG [11], in palmprint recognition. While there are a number of options for palmprint recognition algorithms, the most popular ones rely on DL . Biometric identification and challenges based on computer vision have both made good use of CNN. When it comes to biometrics, form analysis, and image classification, DL shines. Deep learning, in contrast to ML, is able to automatically classify and extract features. The method of feature extraction, matching, and palmprint data processing is the primary focus of the research.

1.1. Deep Learning (DL)

An area of AI that allows computers to handle very complicated problems is deep learning (DL), which investigates ideas and algorithms that can learn independently in a manner that is similar to the human brain. DL is able to identify new features on its own. Nowadays, DL is used in many systems and applications for biometric data identification, and research is underway to mimic the human brain's function, utilising computational rather than biological approaches. With enough pattern recognition in the training data, DL networks may learn to identify almost any identical pattern that isn't in the training set; nevertheless, a large number of patterns are required to train such networks effectively. Some DL networks have been trained to identify various biometric patterns, including fingerprints; these networks go through three stages of training: preprocessing, feature extraction, and data matching [12]. In 1998, Yann André LeCun invented CNNs, a kind of ANN that mimics the way the human brain operates and is used for computer vision tasks[13].

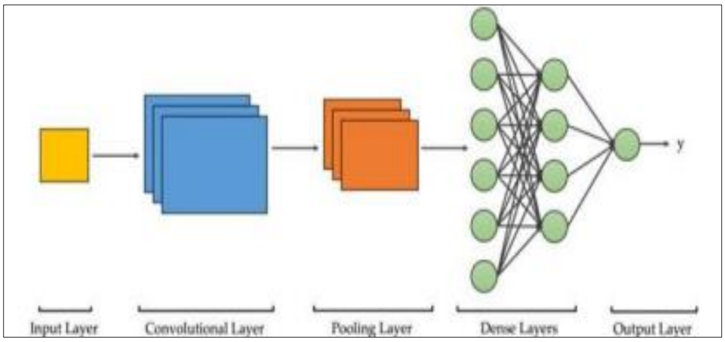

Figure 2 Convolutional Neural Networks [14]

The capacity to link inputs to a hidden layer, which speeds up learning, and the network's ability to extract information from a large dataset made it a popular choice for many biometric applications. The three layers that made up these networks were the convolution, pooling, and fully connected ones. Figure 2 displays these CNN layers [15]. The paper's major contributions:

The present paper discusses palmprint recognition as a critical biometric technique for improving the security and stability of information systems, emphasising its distinct qualities and benefits.

This research investigates an use of DL, namely CNNs and VGG-16, in palmprint identification, emphasising their capacity to do automated feature extraction and classification.

Comparative Model Analysis: The study compares the accuracies of various DL models, like PCNN, VGG16, and Support Vector Machine, in palmprint identification tasks.

The study presents a complete methodology for palmprint recognition, including preprocessing, feature extraction, and classification, as well as insights into the entire pipeline of a typical palmprint recognition system.

The research offers experimental data, including accuracy measurements and graphical representations, demonstrating that CNNs, especially the suggested CNN model, outperform other models in palmprint identification, with an impressive accuracy of 98.5%, respectively.

1.2. Organization of paper

Here is how the article is structured: A literature overview on palm print recognition-based biometric authentication systems is presented in **Section 2**. **Section 3** explains the analytical framework. **Section 4** discusses the comparative results. The results and recommendations for further study are detailed in **Section 5**.

2. Related Work

2.1. Several research in the literature made use of palm prints.

In this research, Smith *et al.*, (2021), a new method has been devised to positively identify individuals using images of their palms. Scannable input images are taken in three dimensions without touching the device. Various transfer learning models are used to compare the suggested system's performance. To address this issue, two CNN-based models are suggested. Starting with the raw image data, they have the first method. The second method involved enhancing the dataset with data augmentation techniques. The dataset is split 65% for training and 35% for testing in both methods. Complete accuracy is the maximum achievable outcome with this suggested method [16].

In this research, Wasmi et al., (2021), built a multi-biometric authentication and identification system utilising a suggested DL technique known as CNN, which relies on palm and finger vein data to address issues like light contrast, time complexity, and accuracy. Additionally, by removing superfluous features, the LDA approach was utilised to identify a most valuable feature. The proposed system outperformed the KNN method with a result of 99%[17].

In, Poonia and Ajmera, (2021), introduces a method for extracting highly discriminative features using a CNN in conjunction with a Gabor filter. Combining CNN with a texture descriptor improves the accuracy of texture-related learning. They run these experiments on the touchless palm-print datasets at CASIA and IIT-Delhi. After applying the approach to the CASIA database, the accuracy is 98.69% and the EER is 0.62%. In comparison to the existing ways, the experimental outcome displays that a suggested method is superior[18].

This study presents a contactless biometric identification and authentication system that combines palm vein and palm print images in a secure (Kala et al., 2021) manner. Among the many parts that make up the system are light-emitting diode (LED) arrays that emit near-infrared light, a "Raspberry Pi SBC" computer, and a cheap CMOS image sensor. The palm prints and vein images are captured simultaneously using real-time IQAC. After that, specific preprocessing methods are used to highlight the relevant vein and palm print features. These system's commercial viability is enhanced because it becomes even more cost-effective when applied on a larger scale[19].

In this study (Sanyal, Chatterjee and Munshi, 2017) features are generated from palm image Cross Wavelet Transformed (XWT) histograms relative to reference palm image. The concept of using a scanner that is in a computer to take a picture of a person's hand is relatively cheap to implement as seen below. The person is then determined having a trained ANN which considers these aspects. The study of palm prints for biometric identification systems employs BFOA, BFVPA with their corresponding adaptive models in identifying the best feature combination. Highly intense experimental studies reveal that the hence proposed approach attains an authentication accuracy of more than 97. 85 percent [20].

In this paper Istiqamah *et al.*, (2017) present a way of palm print recognition based on line hand features, LVQ as the classification neural network, and textural features using GLCM. Furthermore, palm print identification is different from other biometric features in that it has the following advantages: the equipment used for capturing palm prints is relatively cheap and it takes several low-resolution photography and finally it is less officious. Having employed the above suggested strategy in the trials, it was possible to realize a satisfying recognition rate of about 98. 75%[21] .

In this research Awate and Dixit, (2015) Using the PolyU palm print database, experiments are conducted for this endeavour. A total of 250 individuals, including 195 men and 55 females, volunteered to have their palm prints taken. Using the Stock well transform, the characteristics of the fingerprint are retrieved. A remarkable 99% accuracy rate and 91% precision rate are shown by a few of the noteworthy results [22].

Feature extraction methods applied to various palm print datasets are just one of numerous AI-based algorithms and approaches detailed in Table I below. The table also includes methods for classifying and matching palm prints.

Table 1 Related Work Summary for Biometric Palm Print Identification

Ref.	Methods	Results	Research Gaps	Future Work
[16]	3D palmprint image identification using CNN with two approaches (raw image data and data augmentation)	Best result: 95% accuracy	potential overfitting or biases in the training dataset	Analyze the suggested methods' capacity for generalisation using a range of datasets. Examine how various 3D imaging methods affect the performance of the model.
[17]	Multi-biometrics system using CNN on finger vein and palm print, LDA for feature extraction	Proposed system: 99% accuracy, outperforming KNN	system's sensitivity to hyperparameter tuning	Conduct sensitivity analysis to understand the impact of hyperparameters on model performance. Explore the trade-off between feature reduction (LDA) and classification accuracy.
[18]	CNN with Gabor filter for touchless palm-print recognition on CASIA and IIT-Delhi databases	Accuracy: 98.69%, EER: 0.62% on CASIA database	Limited exploration of the model's performance across different databases	Analyze the suggested method's generalization over many datasets. Examine how the parameters of the Gabor filter affect the operation of the model.
[19]	Secure contactless authentication system combining palm vein and palm print, utilising NIR, LED arrays, and Raspberry	Improved economic viability; real-time Image Quality Assessment and Correction	Limited discussion on potential vulnerabilities or security risks	Conduct a thorough security analysis of the proposed system. Explore potential adversarial attacks on the contactless authentication system.
[21]	Line hand feature-based identification, GLCM feature extraction, LVQ artificial neural network as classifier	Identification rate 98.75%	Focused on GLCM and LVQ only; potential bias in feature extraction	Experiment with additional feature extraction techniques and classifiers; test on larger and diverse datasets
[20]	Cross Wavelet Transformed (XWT) histograms, trained ANN, BFOA, BFVPA	Authentication accuracy > 97.85%	Limited to Cross Wavelet Transform; potential overfitting due to ANN	Explore other feature extraction methods; investigate different machine learning models

[22]	PolyU palm print Database, Stock well transform for feature extraction	Accuracy 99%, Precision 91%	Limited sample size (250 volunteers); gender imbalance in dataset	Increase sample size; ensure gender balance; compare Stockwell transform with other feature extraction methods

3. Methodology

The five main components of a palmprint recognition system are the scanner, the database, the feature extraction, and the preprocessing steps. Images of palm prints are captured by the palmprint scanner. During preprocessing, a coordinate system is built up to align Palmprint pictures and segment a section of the image for feature extraction. We can extract valuable characteristics from the preprocessed palmprints by using a feature extraction approach. Using a database of registered templates, a matcher compares two Palmprint characteristics.

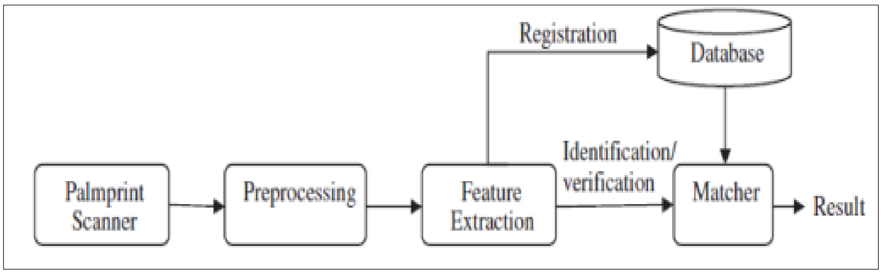

Figure 3 An illustration of a typical palm print recognition system

The contactless palmprint identification system's pipeline is shown in Figure 3. In this case, three main stages are taken after the palmprint picture is prepared: extraction of features, extraction of the ROI, and classification. An introduction to ROI extraction is provided in this section. The first and most important stage in the palmprint recognition process is ROI extraction. Aligning palmprint images is crucial and required since there are global geometric alterations between the images.

3.1. Palmprint scanners

Many different kinds of palmprint scanners, such as digital scanners with video cameras, CCD-based scanners, and others, have been utilized for scanning purposes. When it comes to input and database maintenance, CCD-based palmprint scanners provide the highest quality and most accurate pictures. These scanners also help with alignment by providing instructions on where to insert the palm and how to position it over the scanner. For CCD [23][24], scanner that is based on it needs the right combination of sensors, cameras, and lenses. See this procedure in Fig. 4.

Figure 4 Palm Print scanning process using scanner

3.2. Preprocessing

This step is necessary for aligning different palmprint images and for segmenting the center in order to extract characteristics. Algorithms for preprocessing often consist of five stages, such as binarising [25], the pictures of the palm, then extracting the contours of the figure or hand, then finding important spots or targeted points, and lastly removing the core sections. While most algorithms have comparable first and second stages, the third stage of preprocessing introduces new ways tailored to specific requirements; for example, most of these algorithms employ tangent, bisector, and figure-based methods to differentiate between fingers. The tangent-based method takes into account two boundaries: one between the ring and final figures, and another between the middle and point fingers. These two lines meet at two critical places in the coordinate system, forming an intersection. The several benefits of the tangent base method become apparent as one moves closer to the base of the fingers and the relatively short boundary. Using the figure's midpoint and the line's beginning and ending locations as well as its center of gravity, a bisector-based approach[26] may be constructed.

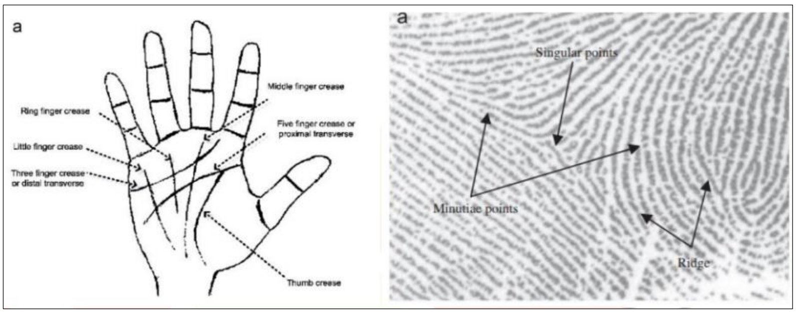

Figure 5 Definitions of palm lines and regions

3.3. Feature Extraction

An aim of a feature extraction step is to create new feature maps from preexisting images in order to produce and identify features and to decrease the number of features in a dataset. One of the most popular methods to reduce data dimensionality and extract features is to utilise a deep neural network, such a CNN. This study makes use of VGG-16, which is built on CNN. CNN has been enhanced to reduce the need for image feature engineering. Deep hierarchical learning, a method for modelling abstract representations, has also been used. Initial layers will identify the basic characteristics. A palmprint's texture, wrinkles, major lines, and ridges are examples of medium-level forms that will be recognized by the intermediate layers; the final layers, on the other hand, will be utilized as an encoder to extract the fingerprint's attributes.

3.3.1. VGG-16

According to ILSVRC 2014, one of the top vision model designs is the VGG16, which is a CNN enlarged by Simonyan and Zisermon. According to VGG16, the convolution layers are derived from a 3×3 step filter, yet the 2×2 filter is consistently used for unnecessary padding and stacking. Two FC (fully connected layers) follow a SoftMax output layer. Nearly one hundred thirty million variables make up this enormous network. Figure 6 displays the VGG16 architecture.

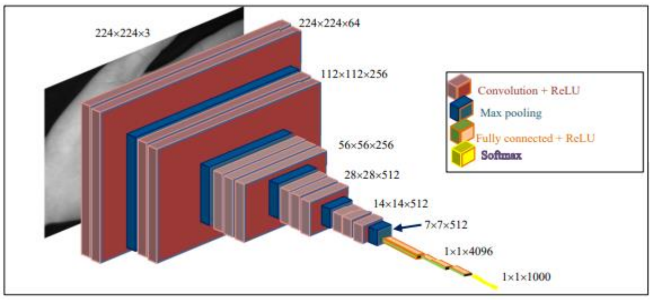

Figure 6 The architecture of VGG16 [27]

The input images for the method have a size of 224 by 224 and are transformed from greyscale to colour. Because this approach employs the VGG16 architecture, which covers three layers instead of just one and uses RGB to detect edges, it is far more accurate at identifying palm prints. VGG16 is the most accurate at identifying edges, which makes it ideal for reading palm prints. Images are divided into 3 groups: 80% for training, 10% for testing, and 10% for validation. After that, they are scaled to match the VGG-16 architecture, a 16-layer network with thirteen (3×3) stacked convolutional layers and two 2×2 maximum pooling layers. These levels are where the Relu activation takes place. Three completely connected layers comprise the majority of the network parameters. Lastly, they have the SoftMax function, which is an essential component of the neural network's activation function[28].

3.4. Classification and Matching

The proposed approach is versatile enough to be employed in both the authentication and identification processes. The identification modality includes a classification phase that uses a k-NN classifier—henceforth referred to as 1-NN—based on the Euclidean distance. Since a 1-NN classifier doesn't have any parameters to tweak and doesn't need training, they went with it. A proposed method's capacity to extract a discriminative template may then be tested in this manner[29]. This allows one to assess a proposed method's capacity to retrieve a discriminative template. Through the use of a matching function -Hand-Hand, they determine a distance among two hand templates -Hand and -Hand in the verification modality. Although several distance metrics may be taken into account, in their study they used the Euclidean distance.

3.5. Palm Print Recognition Using DL

This work's contribution and primary objective is to provide DL models for palm print recognition.

3.5.1. Palm convolutional neural network (PCNN)

Several layers make up the PCNN. The layers that make up this system are as follows: input, convolution, pooling, classification, SoftMax, and fully connected (FC).

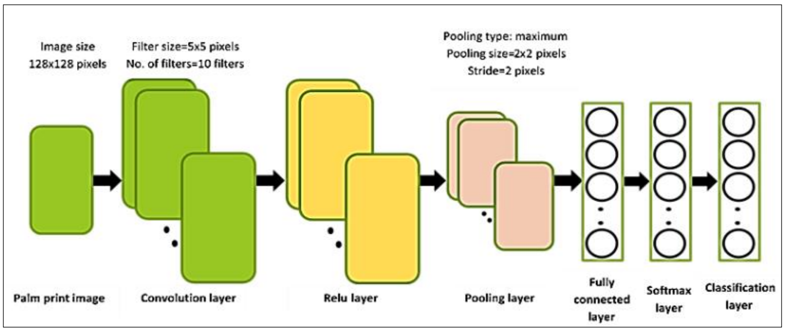

Figure 7 The architecture of the PCNN system[3]

The first step is to modify the input layer so that it can only take in one grayscale segmented palm print image at a time. Every input is 128 pixels x 128 pixels in size. Step two involves using the convolution layer. The characteristics of the grayscale palm print image may be analyzed using this layer. They can see the PCNN's design in Figure 7.

3.5.2. Support Vector Machine

A supervised learning method is the SVM. It offers several different classification and regression processes. Based on the virtual line or curve used to make a conclusion about a given item, SVM may be divided into linear and nonlinear categories. The primary approach involves assigning the provided data to one of n predetermined classes based on the object characteristics and the relevant training outcomes from the past. One definition of the decision surface that divides the classes is[30]:

$$W^T X + b = 0 \tag{1}$$

where W is a weight vector, X is input vector, and b is the bias.

4. Comparative Results and Analysis

This section containing results and a discussion of different techniques. All the details regarding the use of dataset, evaluation metric, comparative analysis of the different DL approaches are illustrated.

4.1. Evaluation Metrics

False positive (FP), true negative (TN), true positive (TP), and true positive (TP) are four measured variables. It is possible to quantify those factors using target and prediction matrices in the following ways: i) TP: your optimistic prediction came true. ii) TN: exactly what they expected, a negative outcome. iii) FN: your negative prediction turned out to be incorrect. iv) FP: your prediction was incorrect, yet it was positive.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \tag{2}$$

Accuracy (AUC): illustrated in Eq. (2), as the percentage of correct predictions compared to the total number of predictions.

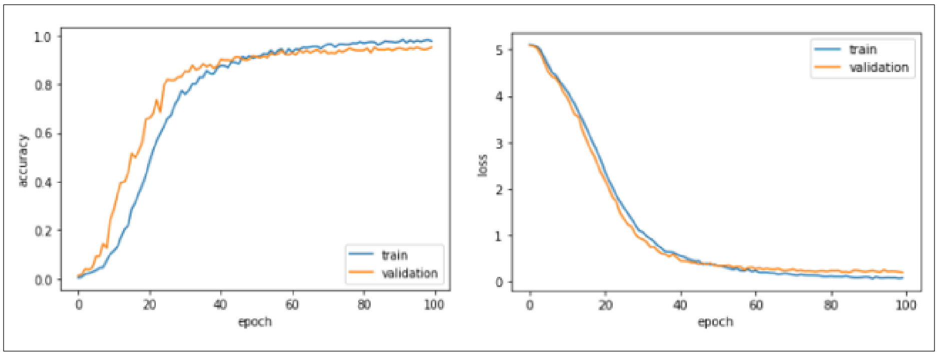

Figure 8 Curve of accuracy/loss of the CNN model

Training with a single dense layer and then freezing all of the CNN layers yields the best results for the CNN Palmprint model. Figure 8 shows the CNN model's 100-epoch training performance. The accuracy plot displays rapid initial increases, with training accuracy approaching 1 and validation accuracy slightly lower. This suggests that there is some overfitting, with excellent learning.

The comparative analysis shown in Table II with accuracy measure included PCNN[3], SVM [31], VGG-16[32] and Design CNN model.

Table 2 Comparison between different deep learning models for Palm Print Recognition

Models	Accuracy
PCNN	97.67
VGG16	97.32
Support Vector Machine	96.31
CNN's	98.5

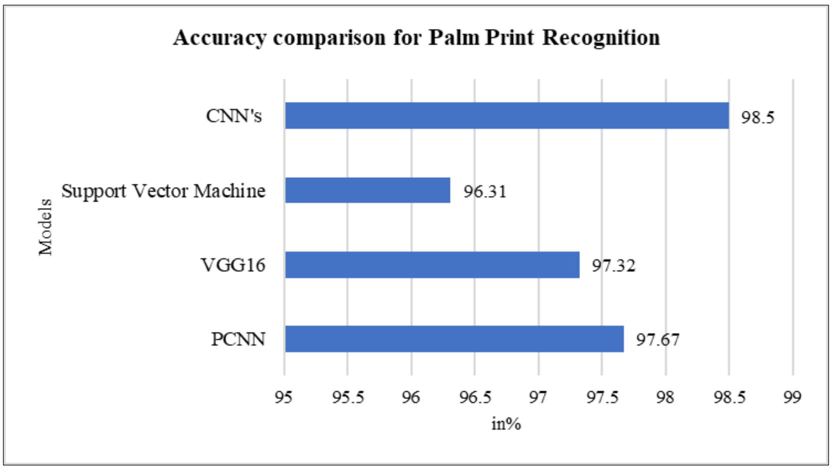

Figure 9 Bar graph of accuracy comparison between different DL models for Palmprints Recognition

Table II and Figure 9 show that Convolutional Neural Networks (CNNs) outperform other deep learning models in palm print identification, with an outstanding accuracy of 98.5%. This outperforms other models, including PCNN (97.67%), VGG16 (97.32%), and Support Vector Machine (SVM) (96.31%). The bar graph vividly shows CNNs' considerable advantage in accuracy, highlighting their ability to capture subtle patterns and characteristics inside palm prints. The findings indicate that CNNs are well-suited for palm print identification tasks, demonstrating their promise as a reliable and accurate solution in biometric applications. When deciding on the best model for a certain application, other considerations such as computing complexity and resource constraints must be considered.

5. Conclusion

Recent years have seen a notable improvement in palmprint recognition. In the current state of supervised deep learning methods, this research suggests an effective paradigm for palmprint recognition. The ROI extraction is successful and the accuracy of the proposed system is satisfactory. A thorough analysis and testing of several DL approaches has been conducted. Deep learning is the most potent technique, and CNN has shown useful in solving biometric and computer vision-based challenges. In this article, they concentrated on palmprint recognition using deep learning methodologies. When compared to existing identification systems, the CNN-based fingerprint recognition system has a high accuracy rate and is predicted to represent a new development in biometric identification techniques. Biometric systems employ convolution neural networks, which have a high accuracy rate. For biometric identification, there are several common CNN-based algorithms. In contrast to previous CNN algorithms, the palm identification method they are applying here uses a region-based fully convolution network, which provides an accuracy of 98.5%. A greater accuracy rate is achieved with a larger training dataset. In the future, studies should consider extracting the hand even from images with unrestricted backdrops by using segmentation methods in conjunction with additional classifiers and distance metrics.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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