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Palmprint Recognition Using Pre-Trained Convolutional Neural Networks

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***Abstract* –**Palmprint recognition (PR) has garnered significant interest due to its distinctive characteristics and potential applications as a robust and secure biometric authentication (BA) method across various domains. This paper introduces a novel approach to enhance PR using pre-trained Convolutional Neural Network (CNN) models. The proposed method process harnesses the capabilities of Deep Learning (DL) and Transfer Learning (TL) to improve palmprint recognition by leveraging state-of-the-art CNN architectures for feature extraction and classification. This proposed method begins by exploring the potential of pre-trained CNN architectures, including ShuffleNet, EfficientNet, and MobileNet, as feature extractors for palmprints. In the next step, extracted feature vectors are compared using the Cosine Similarity (CS) method. The proposed method is thoroughly evaluated through comprehensive experiments. Results of evaluations demonstrate that pre-trained CNN models excel at recognizing palmprints for biometric authentication, establishing their proficiency in this domain. Consequently, this paper illuminates the inherent capabilities of pre-trained CNN models as a potent tool for advancing PR, introducing an innovative facet to BA methodologies.

Keywords – Palmprint Recognition, Convolutional Neural Networks, Biometric Authentication

I. Introduction

BA, which involves identifying individuals through their distinct physical or behavioral characteristics, has now assumed a pivotal role in contemporary security systems. In an era dominated by the need for foolproof access control methods, verification of payments and identity validation, biometric technologies have emerged as indispensable instruments that guarantee privacy and protect sensitive data [1]. PR is an attractive and effective means of authentication among the various forms of BA that have garnered attention [2].

The palmprint, the impression of the palm's unique ridges and valleys, offers a compelling biometric modality due to its several advantageous characteristics [3]. Palmprints present a broader range of applications, including access control to secured facilities, user verification for mobile devices, and forensic analysis. Palmprints are also known for their stability and durability, making them well-suited for long-term BR [4].

The extraordinary development of DL techniques, notably CNNs, is one of the key causes influencing the revival of palmprint recognition. CNNs are highly adept in computer vision tasks like object detection, facial recognition, and picture categorization. These networks are excellent at feature extraction, enabling them to learn discriminative characteristics from raw data [5] automatically. Palmprint Recognition with CNNs promises to be more accurate, robust, and flexible authentication [6].

This paper discusses using pre-trained CNN models already trained on enormous datasets for general object recognition tasks for PR. By utilizing TF, the potential of these pre-trained models as feature extractors for palmprint images is investigated, thereby utilizing their capacity to capture complex patterns and representations. The main goal of this study is to determine whether it is feasible to use pre-trained CNNs for PR and to evaluate how well they perform compared to conventional techniques.

The remainder of this paper is structured as follows: Section 2 presents an overview of the related work in the PR field. Section 3 delves into the detailed explanation of the proposed method. Section 4 is dedicated to presenting the results and discussing the findings. Finally, Section 5 encapsulates the paper with a comprehensive conclusion.

II. Related Works

PR has undergone significant advancements over the years as a branch of BA. This section reviews relevant literature and highlights critical contributions in PR, focusing on approaches utilizing CNNs.

In [7], Matkowski et al. stated that soft biometric characteristics such as gender, ethnicity, or age may provide helpful information for biometric and forensic applications. Researchers used, for example, face, gait, iris, hand, etc., to classify such features. Even though palms have been widely studied for biometric identification, relatively less attention has been paid to palm soft biometrics. In this work, several deep learning models are set and evaluated in gender and ethnic classification scenarios based on palms. The results show that for sex and ethnicity classification in an uncontrolled environment, full-hand images are more suitable than fingerprint images.

In [8], Aberni et al. stated that among the various biometric features that can be extracted from the hand, the palm vein structure is a reliable and reliable source to identify or verify a person's identity. Several methods have been presented in different research based on this fact. To further improve the performance of these methods, this paper presents a new palm vein identification method for personal authentication and identification based on a competitive coding program using a multi-scale local binary pattern with ant colony optimization.

The results obtained in the PolyU-MS database show that the proposed method offers acceptable performance for palm recognition.

Jung et al. [9] have highlighted the expanding role of automatic BA systems in various domains, encompassing applications such as automated identity verification, information capture, security checks, and protection against identity fraud. As biotechnology advances, the market witnesses the emergence of biometric-based identification systems that demand precision and user-friendliness. Among these biometric modalities, palm vein identification stands out, characterized by its ability to analyze the unique features of palm veins. Palm vein recognition, due to its exceptional accuracy, has garnered substantial attention when compared to alternative biometric attributes. This research introduces an innovative non-contact detection system, leveraging a high-performance adaptive background filter to capture palm vein images within the region of interest. The approach utilizes a modified CNN to establish an optimal identification model through rigorous training and testing. Notably, the implemented system operates seamlessly on a resource-constrained Raspberry Pi embedded platform while harnessing the capabilities of cloud computing technology. The experimental outcomes reveal an impressive accuracy rate of 96.54%, underscoring the system's high performance and suitability for real-world applications.

In reference [10], Stanuch et al. introduced a novel approach that employs infrared wavelengths to capture palm images. This innovative method utilizes infrared (IR) and ultraviolet (UV) wavelengths, followed by deep CNN image processing. The network aims to extract distinctive biometric features and perform user authentication. In [11], Jemaa et al. have proposed a method for identity recognition by combining two biometrics from each hand. Biometrics have been selected at two levels: palm and fingerprint. Combining these two models is possible without any restrictions for identity recognition. Additionally, using a new hybrid scheme based on aggregating rank levels leads to achieving acceptable results. In [12], Morales et al. have measured features of the ridge pattern in the palm area that are useful for BA. This review divides the desired area for biometric identification in the palm into three regions. In this work, three feature extraction methods are reviewed, and suitable features for identification are suggested. In [13], Betancourt et al. have segmented the hand's image and identified whether the hand is right or left in video images. In this work, challenges such as blocking of hands or proximity of hands have been examined.

In summary, using CNN models for biometric recognition represents a significant advancement in the field, offering promising results and opportunities for further research. This paper contributes to this work by presenting an in-depth exploration of pre-trained CNN models' efficacy in palmprint recognition and their comparative performance analysis.

III. Proposed Method

This section outlines the proposed method for PR using pre-trained CNNs. The proposed approach aims to maximize the accuracy and effectiveness of PR by utilizing pre-trained CNN architectures and the power of TL.

A. *Pre-trained CNN Models*

CNNs already trained on large-scale picture datasets like ImageNet are known as pre-trained CNNs. Edges, shapes, and textures are just a few examples of the essential features that these models have learned to identify and extract from photos. Utilizing pre-trained CNNs can be highly beneficial for various computer vision applications, such as semantic segmentation, object recognition, and image classification [5, 14-16]. The following provides a summary of several pre-trained models utilized in this paper.

ShuffleNet is a highly effective CNN architecture that creatively uses bottleneck blocks, group convolution, and channel shuffling. With its competitive performance and significant reduction in computational costs, this design is an excellent option for resource-constrained applications like edge computing and real-time object detection on mobile devices [17].

Model size, accuracy, and computing efficiency are all factors that EfficientNet aims to balance. It uses a compound scaling technique that gradually increases network depth, width, and resolution to improve model performance. EfficientNet uses fewer processing resources than other models while producing cutting-edge outcomes on various computer vision tasks. It helps applications with low computational requirements [18].

MobileNet is designed for embedded and mobile vision applications. The typical convolution is divided into depthwise and pointwise convolutions using depthwise separable convolutions. While maintaining comparable accuracy, this method lowers the number of parameters and computational expense. For real-time image processing on devices with limited resources, MobileNet is appropriate [19].

B. *Cosine Similarity*

CS is a measure based on calculating the cosine of the angle between two vectors. If the two vectors match (in this criterion, the sign of complete similarity) and the angle between the two vectors is zero, its value will be equal to 1. At the lowest degree of similarity between the two vectors, that is, if the angle between the two vectors is 180 degrees, the result of this criterion will be -1. This criterion is one of the most widely used in image and text processing. The equation for CS of two vectors, A and B, is as follows:

$$CS(A,B) = (A \cdot B) \,/\, (||A|| * ||B||)$$

where:

- $(A \cdot B)$ is the dot product of two vectors.
- $||A||$ is the Euclidean norm of vector A.
- $||B||$ is the Euclidean norm of vector B.

The CS formula calculates the cosine of the angle between two vectors, which indicates their similarity [20].

C. *Problem-Solving*

PR aims to recognize people from the distinctive features and patterns in their palmprints, which are stable and consistent over time. As a biometric authentication method, PR takes distinctive patterns and features from a person's palm to confirm their identity. The proposed approach is intended to complete this task precisely and successfully using pre-trained CNN models. Figure 1 provides a visual representation of the proposed method, elucidating the sequential stages of the process. So, in the following, a concise overview of the key steps involved in this method is explained.

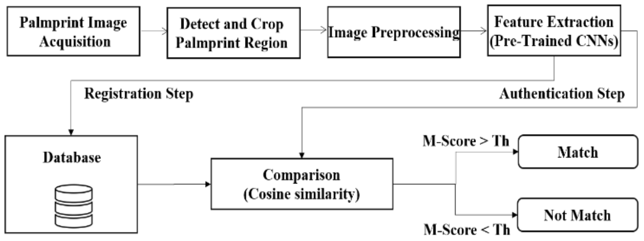

Fig. 1 The architecture of the proposed method.

Taking a high-resolution picture of the palm is the first step in the process. The use of specialized palmprint scanners or imaging equipment guarantees the high quality and clarity of the palmprint representation in this image. The acquired palmprint image is subjected to several preprocessing steps during the preprocessing phase. First, Detecting the image's palmprint region is necessary to isolate the relevant features. The RobustPalmRoi technique is used for palmprint detection [21]. The photo is then cropped so that the palmprint area is the only thing in focus. The palmprint image is finally resized to a standard size of 224x224 pixels. These preprocessing procedures improve the consistency and suitability of palmprint images for additional analysis.

Feature extraction is a critical phase where the significant and distinctive attributes from the palmprint image are extracted. The proposed method utilizes the capabilities of pre-trained CNN models featuring cutting-edge architectures like MobileNet, ShuffleNet, and EfficientNet for feature extraction. These models have been pre-trained on vast datasets and are adept at learning hierarchical and abstract features. From these models, feature vectors with a dimensionality of 512 are extracted. These feature vectors capture the distinct traits of palmprints, facilitating a robust means of distinguishing individuals effectively.

The palmprint image comparison is based on the extracted feature vectors. The suggested technique measures how similar two palmprint images' feature vectors are by using the CS method. CS method is a reliable and understandable similarity metric. This method calculates the cosine of the angle between two feature vectors.

Making decisions based on the CS result is the final step. This step involves setting a threshold value. If the CS value between two images surpasses this threshold, the images are considered matched; conversely, if the CS result falls below the threshold, the system concludes that it is not a match, indicating different individuals.

The proposed method comprises two fundamental steps: registration and authentication. In the registration phase, the feature vector extracted from the input data is stored within the database for future reference. In the subsequent authentication step, the acquired feature vector is compared to the existing feature vectors in the database using CS. The authentication process is completed when the match score surpasses a predefined threshold. This two-step procedure forms the core of the proposed methodology, facilitating reliable and secure user verification.

The suggested PR method combines image preprocessing, deep feature extraction using pre-trained CNN models, and CS comparison to authenticate people based on their distinctive palmprint patterns. This approach provides a strong and trustworthy way to confirm identity, making it appropriate for various applications, from biometric authentication to secure access control.

IV. Result And Discussion

This section presents the simulation results of the palmprint recognition system utilizing pre-trained CNNs. An inclusive evaluation was conducted to assess the system's performance in terms of accuracy and efficiency.

A. Dataset

Tongji Contactless Palmprint Dataset [22] has been used to evaluate the proposed method. This dataset established a large-scale contactless palmprint image dataset. This dataset includes images collected from 300 volunteers, including 192 males and 108 females. Among them, 235 subjects were 20~30 years old, and the others were 30~50 years old. Samples are collected in two separate sessions. Each session asked the subject to provide ten images for each palm. Therefore, 40 images from 2 palms were collected from each subject. In total, the database contains 12,000 images captured from 600 different palms. The average time interval between the first and the second sessions was about 61 days. The maximum and minimum time intervals were 106 and 21 days, respectively [22]. Figure 2 visually represents a dataset sample, showcasing palmprints from both the left and right hands. Within the scope of this study, exclusively images of the left hand were utilized to train the models used in the proposed method.

Fig. 2 Palmprints from both the left and right hands.

B. Implementation and Results

For the implementation of the proposed method, the PyTorch library as a foundational tool is used [23]. The models' development occurs on a computing system equipped with an eight-core Intel i7 processor, 32 GB of RAM, a 1 TB SSD hard drive, and an NVIDIA GeForce GTX 3070 Ti graphics card. The dataset is partitioned into two categories: training and evaluation, facilitating the model implementation process. In this simulation, the models mentioned above undergo training under consistent conditions. The optimization method employed is Adam's optimization algorithm [24], with an initial learning rate of 0.001. The model training procedure undergoes 15 iterations in total.

In the assessment of the proposed method, involved an examination of parameters associated with model training, encompassing the analysis of training duration, validation accuracy, and model size. Validation accuracy is a fundamental metric that reflects the model's ability to accurately identify palmprints within a given dataset. A higher validation accuracy indicates a more dependable model for palmprint recognition, a crucial aspect in authentication and security applications. The result presented in Table 1 illustrates that utilizing pre-trained CNNs substantially improves validation accuracy, establishing the proposed method as a compelling option for palmprint recognition tasks.

Table 1 Assessing Three Pre-Trained Models with the Proposed Method

	Val-Accuracy	Val-Loss	Training Duration	Model Size
MobileNetV2	0.9955	0.0173	28M+ 37S	13.3 MB
ShuffleNetV2	0.9941	0.0946	28M + 2S	4.8 MB
EfficientNetB0	0.9947	0.0115	29M + 1S	20.5 MB

Training time is another essential factor in evaluating the model's practicality. Efficient training is crucial for deploying a model in real-world scenarios. By using almost lightweight CNN models, the proposed method reduces the time required for training, making the model more time-efficient. This feature is precious for applications with critical rapid response and real-time performance. The results in Table 1 highlight Shufflenet as having the shortest training time among the models examined.

Model size is also a critical consideration, especially in resource-constrained environments. A smaller model size can be advantageous regarding storage, memory, and deployment. The study outlines that lightweight CNN models lead to a more compact model size while preserving high PR performance. This makes the proposed method suitable for deployment on devices with limited storage and computational resources.

In summary, a close examination of the data presented in Table 1 concludes that ShuffleNet emerges as a pragmatic choice for real-time applications characterized by limited computational resources. This selection proves favorable because it delivers satisfactory accuracy while maintaining a compact model size and minimizing the required training time.

V. CONCLUSION

This paper has investigated the PR field and proposed a new approach to improve its capabilities by incorporating pre-trained CNN models. PR is gaining attention because of its unique features and potential applications as a robust and secure method of BA in various industries. The proposed approach combines the power of DL and TL to enhance PR by leveraging state-of-the-art CNN architectures to extract features from PR data and classify them to identify trends. It uses the CS method for the comparison of feature vectors. This study has shown that pre-trained CNN models can improve PR systems, introducing a new approach for BA systems. These models could make PR systems more accurate, reliable, and secure. This study evaluated the performance of three pre-trained CNN models for palmprint recognition: ShuffleNet, EfficientNet, and MobileNet. The models were fine-tuned on the Tongji Contactless Palmprint dataset to improve their accuracy on palmprint data. The results showed that all three models achieved high accuracy, with MobileNet performing the best. The findings suggest that pre-trained CNN models are a promising approach for PA in BA applications. Considering all three evaluation criteria, the superior performance of ShuffleNet becomes evident. It excels by delivering a compact model size and shorter training duration, all while retaining a commendable level of accuracy.

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