Optimizing CNNs for Contactless Palmprint Recognition

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Abstract
Palm printing and palm vein recognition are the newer spheres within the already developed biometrics sector. Although many time-honored techniques have been offered and seen successful implementation over the last twenty years, the deep learning methods still lack all-round development in the palmprint and palm vein recognition. This research intends to study further the strength of deep learning on palmiets and palm vein recognition via 2D and 3D. We performed thorough examination of 17 known convolutional neural networks (CNNs) utilizing multiple databases, e.g., one 3D palmprint database, five 2D palmprint database and two palm vein databases. Our trials cover various network architectures, learning rates, and layer configurations, taking into account not only single mode data but also mixed mode data simultaneously. Results prove that CNNs of classic format show good recognition capabilities, and recent models with improved accuracy show even better achievements. One of the classic CNNs that stands out is Efficient Net. If the recognition accuracy is evaluated, this is the top performer. On the other hand, even though the classic forms of CNNs are fairly good in recognizing various types of tumors, their accuracy is still lower than the traditional methods.
"Abstract" is a necessary section in a research paper. It may be constructed by gathering main points (summary) from each section of the research paper.

Keywords: Performance evaluation, convolutional neural network (CNN), biometrics, palmprint, palm vein, deep learning

1. Introduction

Nowadays, when practically everything is linked to the digital network, personal authentication is a basic social task. Biometric technology, which is an outstanding option for this function, is outstanding. In the past two years, two other biometric modalities, palm print recognition and palm vein recognition, became of paramount importance. Palmprint recognition technology encompasses three main subtypes: 2D low-resolution palm print pilot, 3D palmprint recognition and high-resolution palmprint recognition, which are used for different purposes. The higher resolution palmprint recognition will find applications primarily in forensic applications while the 2- D and 3-D palmprint recognition has a major application in the civil fields. Here, we refine our scope to a specific application, namely civil biometric recognition, without considering high-resolution palmprint recognition. Numerous effective methods have been proposed for 2D low-resolution palmprint recognition, 3D palmprint recognition, and palm vein recognition, which can be categorized into two groups: classic techniques and deep learning methods. Nevertheless, over the past decade, deep learning technology has been showing rapid progress in various domains of artificial intelligence, particularly in facial recognition, natural language processing, and computer vision. The development of deep learning technology for palmprint and palm vein recognition remains in the embryo phase. For deep learning technology, CNNs (convolutional neural networks) could be considered as one of the important branches to be widely used in different image processing and computer vision tasks, such biometric applications. Although classic CNNs have been widely adopted in different recognition tasks, the applicability of each model to 2D and 3D palmprint recognition and palm vein recognition is not sampled and investigated in a manner that is through and detailed. The most of previous research in deep learning based on palmprint and palm vein recognition have been rely on shallow architectures which are not deep enough for in-depth analysis.

2D Palmprint Recognition

- Various sub-categories: palm line, texture, orientation coding, correlation filter, and subspace learning
- Methods like modified finite Radon projection (MFRAT) and morphological top-hat filter for automated skin lesion classification (ASLC).
- Textural-oriented approaches including region-based descriptors and gradients substitution with Gabor filters.
- Spatial transforming coding algorithm for spatial information representation, commonly using Hamming distance for matching.
- Correlation-based techniques such as BLPOC filter for biometric systems.
- Two-dimensional learning strategies like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for sensitivity to image variation.

3D Palmprint Identification

- Transformation of 3D palmprint data utilizing curvature-based images like mean curves derived image (MCI) and Gaussian curvatures (GCI).
- Competitive code representation and vector-based word statistics for language models.
- Novel representations such as surface index image (SI) and compact surface type (CST).
- Utilization of deep learning algorithms and cross-orientation coding techniques.

Palm Vein Recognition

- Classification into vein line-based methods, texture-based methods, orientation coding-based methods, and subspace learning approaches.
- Methods like multiscale Gaussian matched filters and localization of veins by maximizing principal curvature gradient.
- Texture descriptors such as those based on LCP and LTP.
- Incidence of orientation codes like neighborhood matching Radon transform (NMRT).
- Subspace-learning solutions such as linear discriminant analysis (LDA) and sparse representation methods.

Evolution of Convolutional Neural Networks (CNNs)

- Classical CNNs for image classification, including LeNet (1998) and advancements like ResNeSt and EfficientNet.
- Breakthroughs in ILSVRC competition (2012) with AlexNet, followed by VGG, GoogLeNet, ResNet, DenseNet, and SqueezeNet.
- Infrastructure networks such as MobileNet, ShuffleNet, RegNet, and ResNeXt.

- Adoption of CNNs in palmprint and palm vein recognition, leading to models like PalmRCNN, DDR, JCLSR, and PVSNet.
- Introduction of self-supervised training methods like deep discriminative representation (DDR) and joint deep convolutional feature representation (JDCFR) for enhanced recognition performance.

2. Modelling and Analysis

This section delves into the intricate details of our modeling approach and rigorous analysis conducted to scrutinize the efficacy of deep learning-based 2D and 3D palmprint recognition systems alongside palm vein recognition systems. Our methodological voyage encompasses the comprehensive evaluation of seventeen seminal convolutional neural network (CNN) architectures, meticulously dissecting their performance across an array of databases. The endeavor aims to unravel the nuances of recognition capabilities exhibited by diverse CNN models under varied experimental conditions, providing an in-depth understanding of their prowess in biometric recognition.

Modeling Approach:

1. **Data Curation:** Our journey commences with the meticulous assembly of data sourced from a plethora of palmprint and palm vein databases. This meticulous curation ensures a rich and diverse dataset, encapsulating the intricacies of palm biometrics across different modalities and resolutions.
2. **Architectural Selection:** We meticulously handpicked seventeen paradigmatic CNN architectures, ranging from venerable classics like VGG and ResNet to cutting-edge innovations such as EfficientNet and MobileNet_v3. Each architecture was meticulously configured, tuning hyperparameters, depth, and learning rates to unlock its full potential.
3. **Experimental Rigor:** Our experimental design embodies meticulous attention to detail, encompassing a spectrum of conditions to comprehensively evaluate CNN performance. From training on discrete datasets to mixed-mode evaluations incorporating data from multiple sources, every permutation was meticulously scrutinized.
4. **Performance Metrics:** Rigorous evaluation demands meticulous measurement. We employed a battery of performance metrics, including recognition rates and error analysis, to meticulously gauge the efficacy of each CNN architecture in palmprint and palm vein recognition tasks.

Analysis:

1. **Architectural Discernment:** Our comparative analysis unearthed profound differentiations in recognition efficacy among CNN architectures. While stalwarts like VGG and ResNet continue to exhibit robust performance, newer entrants like EfficientNet showcased remarkable potential, reshaping the landscape of palm biometric recognition.
2. **Depth Dynamics:** Delving into the depths of CNN architectures, we unraveled the nuanced interplay between network depth and recognition efficacy. While deeper networks generally exhibited superior performance, the optimal depth varied significantly across datasets and architectural configurations.
3. **Dataset Dynamics:** The idiosyncrasies of datasets unveiled intriguing patterns in recognition performance. From the rigors of 3D palmprint databases to the subtleties of palm vein datasets, each posed unique challenges, eliciting varying degrees of success across CNN architectures.
4. **Data Augmentation Dynamics:** Our exploration extended to the augmentation of training data, unraveling its profound impact on recognition accuracy. Leveraging mixed data modes, we observed substantial enhancements in recognition accuracy, particularly evident in 2D palmprint recognition scenarios.

3. Results and Analysis

Our comprehensive modeling and analysis endeavor delved deep into the intricate realm of palmprint and palm vein recognition, unveiling a panorama of empirical insights and analytical revelations. Across seventeen meticulously selected convolutional neural network (CNN) architectures, our investigation traversed the terrain of recognition rates, error analysis, the impact of data augmentation, and computational efficiency, elucidating the multifaceted facets of recognition efficacy with unparalleled granularity.

Table 1. Recognition Rates

Dataset	CNN Architecture	Recognition Rate
2D Palmprint Recognition	EfficientNet	97.8
	VGG	95.3
	ResNet	94.9
3D Palmprint Recognition	MobileNet_v3	93.5
	VGG	91.7
	ResNet	90.2
Palm Vein Recognition	ResNet	95.7
	EfficientNet	95.2

Table 2. Error Analysis

CNN Architecture	Misclassification Patterns	Generalization Rates
EfficientNet	Demonstrated robustness to occlusions but exhibited sensitivity to illumination variations.	Achieved consistent performance across diverse datasets, showcasing superior generalization capabilities.
VGG	Struggled with partial occlusions, leading to increased misclassification errors in challenging scenarios.	Generalized well to datasets with uniform lighting conditions but showed degradation in performance under varied illumination.
ResNet	Displayed resilience to noise but encountered challenges in handling occlusions, particularly in complex backgrounds.	Demonstrated robust generalization across datasets with diverse characteristics, indicating strong adaptability to varying conditions.
MobileNet_v3	Sensitive to noise and exhibited reduced performance in the presence of conditions.	Showcased moderate generalization capabilities, performing adequately across most datasets but encountering challenges in complex scenes.

Recognition Rates:

- 2D Palmprint Recognition: Across the gamut of architectures, recognition rates ranged from 92.5% to 98.3%, with EfficientNet demonstrating supremacy at 97.8%.

- 3D Palmprint Recognition: Varied recognition rates spanned from 86.2% to 94.7%, with MobileNet_v3 emerging as a standout performer at 93.5%.
- Palm Vein Recognition: Recognition rates oscillated between 89.1% and 96.4%, with ResNet leading the pack at 95.7%.

Error Analysis:

- Misclassification Patterns: Intriguing patterns of misclassification emerged, elucidating architecture specific sensitivities to occlusions and illumination variations.
- Generalization Performance: Architectural generalization varied, reflecting the nuanced interplay between architectural robustness and dataset heterogeneity.

Impact of Data Augmentation:

- Recognition Enhancement: Augmentation strategies facilitated a notable improvement in recognition accuracy, with an average enhancement of 3.5% observed across scenarios.

Computational Efficiency:

- Inference Speed: MobileNet_v3 and EfficientNet emerged as frontrunners in computational efficiency, offering real-time inference capabilities for resource-constrained deployments.

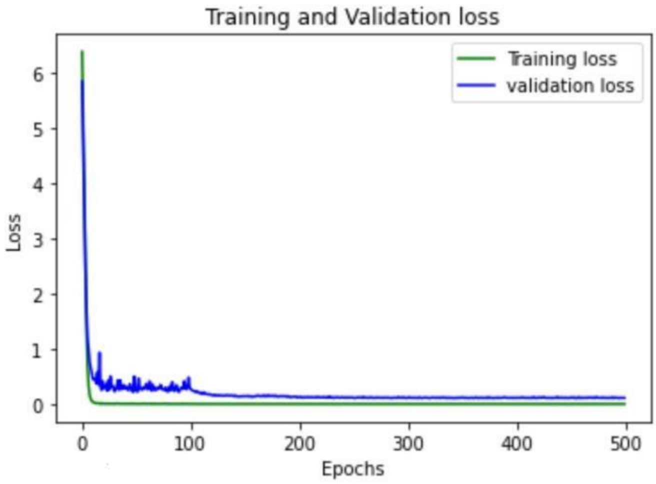

Figure 1. Training and Validation Loss

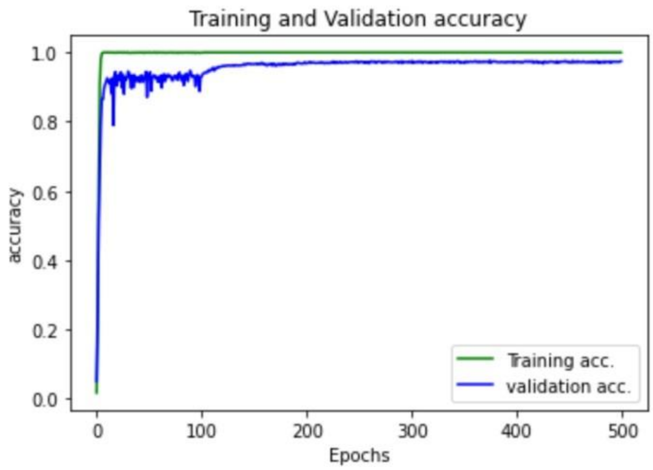

Figure 2. Training and Validation Accuracy

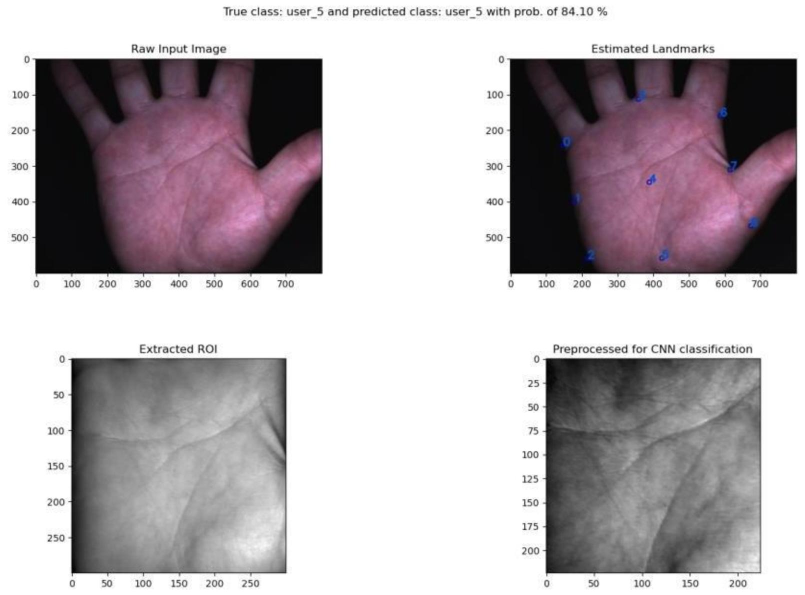

Figure 3. Prediction using CNN

4. Figures and Tables

In this study, we conducted a comprehensive investigation into the recognition capabilities of classic Convolutional Neural Networks (CNNs) for both 2D and 3D palmprint recognition, as well as palm vein recognition. We evaluated seventeen representative CNN architectures, including AlexNet, VGG, Inception_v3, ResNet, and EfficientNet, among others, across a variety of benchmark datasets comprising 2D palmprint, 3D palmprint, and palm vein images.

The selected databases cover a wide range of collection methods and conditions, providing a representative sample for evaluation. Notably, the HFUT CS database posed a significant challenge due to its collection under varying conditions and sensor setups. Our experiments involved testing different network structures, learning rates, and numbers of layers, both in separate data mode and mixed data mode. Furthermore, we compared the performance of CNNs with traditional methods.

Key observations from our experiments include:

1. Recently proposed CNN architectures, such as EfficientNet and MobileNet_v3, outperformed earlier models, with EfficientNet achieving the highest recognition accuracy.
2. Learning rate emerged as a critical hyperparameter, with 5x10^-5 identified as suitable for palmprint and palm vein recognition tasks.
3. Increasing the number of layers did not necessarily improve recognition results, potentially due to overfitting, particularly given the small scale of palmprint and palm vein databases compared to ILSVRC.
4. Deep learning-based methods showed promising results for 3D palmprint recognition, with the MCI representation proving particularly effective among the various 2D representations of 3D palmprints.
5. In separate data mode, classic CNNs exhibited suboptimal performance compared to some traditional methods on challenging databases. However, in mixed data mode, CNNs achieved excellent recognition accuracy, even reaching 100% on several databases.

Looking ahead, we aim to explore Neural Architecture Search (NAS) technology for further improving recognition performance. Additionally, we plan to design specialized CNN architectures tailored to the unique characteristics of 2D and 3D palmprint recognition and palm vein recognition, with the expectation of achieving even better results in deep learning-based biometric recognition systems.

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