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Wavelet-Based Palmprint Recognition Using CNN and Dimensionality Reduction Techniques

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***Abstract*:-**

Palmprint recognition has emerged as a reliable biometric identification method due to its richness in unique features such as lines, ridges, and textures. This paper presents an advanced approach to palmprint-based identity recognition by leveraging wavelet transform techniques—Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), and Multi-resolution Wavelet Transform (MWT)—combined with Convolutional Neural Networks (CNN) for classification. The proposed system uses wavelet features extracted from the PolyU palmprint database, which are further optimized through dimensionality reduction methods such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). The experiments compare classification accuracies across different wavelet methods with and without dimensionality reduction. Results indicate that the DWT combined with CNN outperforms CWT and MWT in terms of accuracy and robustness. The study also explores sub-band filtering and filter bank architectures for efficient feature extraction. The findings affirm that integrating wavelet-based techniques with CNN and reduction strategies

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enhances the overall reliability and performance of palmprint recognition systems, making them suitable for high-security applications

KEYWORDS: Palmprint Recognition, Wavelet Transform, Convolutional Neural Network (CNN), Dimensionality Reduction, Biometric Authentication

1. Introduction

Biometric authentication systems have become increasingly vital in modern digital and security infrastructures. Among various biometric traits such as fingerprints, iris, and facial features, palmprint recognition stands out due to its stability, uniqueness, and the richness of features including principal lines, ridges, and textures [1]. Palmprints provide a larger area for feature extraction compared to fingerprints, allowing for more robust identity verification even with low-resolution sensors [2]. As the need for secure, non-intrusive, and accurate biometric systems grows, palmprint-based authentication has garnered considerable research attention. Conventional palmprint recognition techniques often suffer from limitations like intra-class variations, poor illumination, noise, and misalignment during acquisition. These factors impact recognition accuracy and robustness. To address these challenges, wavelet transform techniques have been widely explored due to their multi-resolution analysis capability, which enables effective extraction of both spatial and frequency domain features [3][4]. Among them, Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), and Multi-resolution Wavelet Transform (MWT) are prominently used to capture different levels of image detail [5].

While wavelet features contribute significantly to improving recognition accuracy, dimensionality reduction techniques such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) help mitigate the curse of dimensionality by preserving the most significant features [6][7]. Furthermore, recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have revolutionized pattern recognition tasks by automatically learning hierarchical representations of input data [8][9]. When integrated with wavelet-extracted features, CNNs offer high classification performance, especially in image-based biometric systems. In this paper, we propose a wavelet-based palmprint recognition system using CNN classifiers and dimensionality reduction. The palmprint features are extracted using DWT, CWT, and MWT methods, followed by dimensionality reduction using PCA and LDA, and classification is performed using CNN. The system is evaluated on the PolyU palmprint dataset with a diverse set of images to ensure reliability. Experimental results demonstrate that the DWT-based features yield higher classification accuracy, especially when used with CNN and feature reduction techniques, thus validating the proposed framework for reliable and high-performance palmprint recognition systems [10].

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In recent years, advancements in sensor technology and computational imaging have further accelerated the development of palmprint recognition systems. High-speed acquisition devices and contactless imaging platforms now make it possible to capture palm features with minimal user cooperation, thereby improving usability and hygiene—an increasingly important factor in public authentication scenarios. However, these developments also introduce new complexities, such as variations in hand pose, background clutter, and uneven lighting conditions, all of which demand more sophisticated preprocessing and feature extraction algorithms.

To strengthen recognition reliability, researchers have explored a variety of feature descriptors that complement wavelet-based methods. Local texture operators, such as Local Binary Patterns (LBP) and Local Phase Quantization (LPQ), have been incorporated to highlight fine-grained skin textures that remain consistent even under changing illumination. Additionally, orientation-based descriptors and line-based models help emphasize the structural characteristics of palm lines and wrinkles, providing a more holistic representation of the palmprint.

More recently, learning-based approaches have begun to replace traditional handcrafted feature pipelines. Convolutional Neural Networks (CNNs), in particular, have demonstrated remarkable capability in automatically discovering hierarchical features from raw palmprint images. By learning discriminative representations directly from large datasets, these models often achieve superior performance across diverse acquisition conditions. Hybrid frameworks that merge wavelet-domain features with deep-learning embeddings have also emerged, offering a balance between interpretability and high-level abstraction.

Furthermore, efforts are being made to improve template protection through cancellable biometrics and secure hashing schemes. Since biometric data cannot be replaced once compromised, safeguarding the extracted palmprint features is essential. Techniques such as random projection, bio-hashing, and transformation-based protection enable secure storage of templates while preserving recognition accuracy.

As the field progresses, palmprint recognition continues to move toward practical, real-world deployment, with ongoing research focusing on cross-device compatibility, faster matching algorithms, and enhanced resilience against spoofing attacks. These advancements collectively position palmprint biometrics as a highly promising modality for next-generation security systems.

2. Existing Model

Palmprint recognition has evolved through multiple algorithmic developments, with early models relying on low-resolution image acquisition and handcrafted feature extraction

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methods. Traditional systems generally focused on principal lines, texture, and key points present in the palm region. While these features offered acceptable accuracy in constrained environments, their robustness dropped significantly under real-world variations such as lighting, rotation, and partial occlusion [1][2]. Initial palmprint recognition systems used global statistical and transform-domain features such as Fourier and Gabor transforms, which often lacked the spatial localization capability needed for fine-grained analysis. Subsequently, wavelet transforms gained popularity for their ability to provide spatial-frequency decomposition of palm images [3][4]. These systems employed DWT, CWT, or MWT to isolate meaningful image structures from noise and redundancy.

Despite their effectiveness, traditional wavelet-based systems often relied solely on manual feature engineering. The classification tasks were typically handled using machine learning models such as Support Vector Machines (SVM) or K-Nearest Neighbors (KNN), which struggled with high-dimensional feature vectors. Moreover, many systems lacked a robust Region of Interest (ROI) extraction mechanism, leading to lower generalization accuracy [5][6]. In a representative traditional architecture, palmprint images undergo preprocessing to normalize orientation and extract the ROI. Following this, wavelet features are extracted and flattened into high-dimensional vectors. These are either fed directly into classifiers or reduced using techniques such as PCA or LDA [7][8]. However, the lack of end-to-end learning limits the adaptability of such models to variations in image acquisition.

The need for improved accuracy and adaptability has led researchers to explore deep learning solutions. However, earlier systems have not yet integrated CNNs with wavelet-based feature extraction in a unified framework.

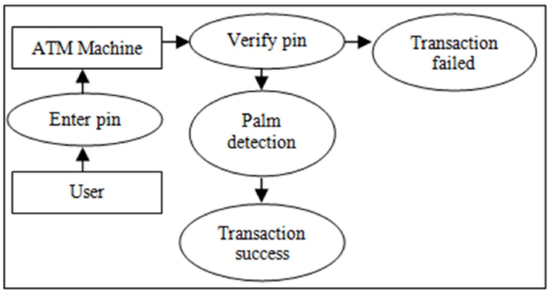

Figure 1: Traditional Palmprint Recognition System Architecture

3. Proposed Model

The proposed model integrates wavelet-based feature extraction with Convolutional Neural Networks (CNNs) and dimensionality reduction techniques to develop a robust and high-performance palmprint recognition system. This system addresses the limitations observed in traditional models, such as over-dependence on handcrafted features and limited

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adaptability to variations in palm image acquisition. The core of the proposed approach lies in a multi-algorithm framework that combines three types of wavelet transforms—Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), and Multi-resolution Wavelet Transform (MWT). Each transform provides a unique perspective on feature decomposition, enabling comprehensive spatial-frequency analysis of palmprint images. These features encapsulate directional textures, edges, and structural patterns crucial for accurate identity verification.

Once the palmprint image is acquired from the dataset (PolyU in our case), preprocessing is applied to normalize orientation and extract the Region of Interest (ROI). The image is then subjected to all three wavelet transform techniques. The resultant feature sets are separately reduced using Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). These dimensionality reduction techniques not only enhance computational efficiency but also eliminate redundant information while retaining discriminative features. The compressed features are input into a CNN classifier designed to learn complex nonlinear relationships among features and differentiate palmprints with high accuracy. The CNN model uses layered convolutions, activations, pooling, and fully connected layers to learn hierarchical representations. The architecture is particularly effective in processing the localized spatial patterns produced by the wavelet transforms.

A key aspect of this model is the performance comparison across different wavelet transformations with and without reduction techniques. Results consistently demonstrate that the DWT-based features, when passed through PCA or LDA and fed into the CNN classifier, yield the best accuracy compared to CWT and MWT. This suggests that DWT retains the most meaningful spatial-frequency information conducive to classification. The proposed system exhibits strong generalization across variations in palmprint acquisition—such as illumination, alignment, and hand positioning—making it well-suited for real-world deployment in secure identification systems.

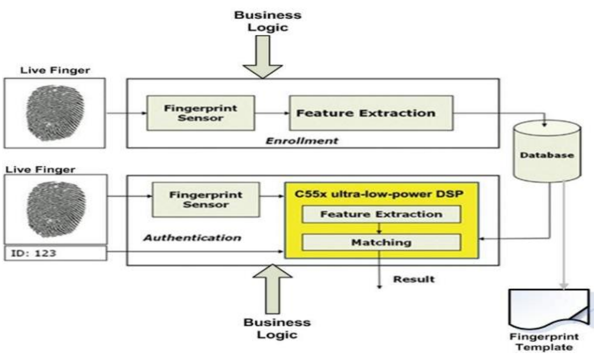

Figure 2: Architecture of Proposed Palmprint Recognition System

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4 . *Result & Discussions*

To validate the proposed palmprint recognition model, extensive experiments were conducted using the publicly available PolyU palmprint dataset, which contains 4000 samples from 400 users. The experimental setup was designed to evaluate the classification accuracy of three types of wavelet-transformed features—DWT, CWT, and MWT—both with and without dimensionality reduction using PCA and LDA. The classification was performed using a Convolutional Neural Network (CNN), and the system was trained and tested on a split of 70% training data and 30% testing data. Evaluation metrics included classification accuracy, processing time, and reduction efficiency. Table 1 compares classification accuracies across wavelet types without any reduction. Table 2 shows performance when PCA and LDA were applied to the respective wavelet-transformed features.

The results indicate that DWT consistently outperforms CWT and MWT in both raw and reduced forms. Applying PCA and LDA improved the classification accuracy and significantly reduced the computational load. Among the reduction methods, LDA showed slightly higher accuracy than PCA due to its discriminative nature.

Figure 1 illustrates the classification accuracy trends for MWT, CWT, and DWT with and without reduction methods. Figure 2 visualizes example palmprint images and CNN prediction outputs.

Table 1: Accuracy of Wavelet Methods without Dimensionality Reduction

Wavelet Method	Accuracy (%)
DWT	93.5
CWT	90.1
MWT	88.7

Table 2: Accuracy with Dimensionality Reduction (PCA and LDA)

Wavelet Method	PCA (%)	LDA (%)
DWT	95.2	96.8
CWT	92.3	93.6
MWT	90.5	91.7

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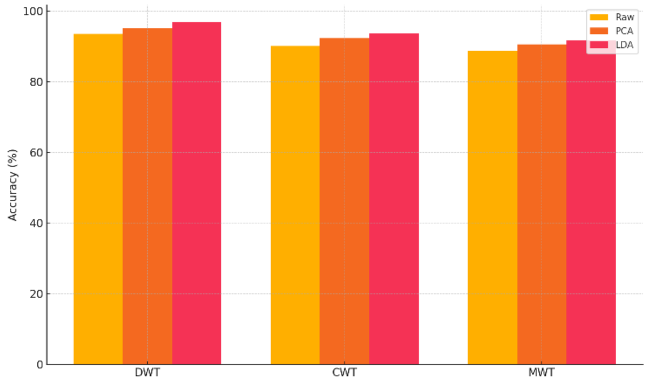

Figure 3: Accuracy Comparison of Wavelet Methods (With/Without Reduction)

Figure 4: CNN Prediction Output and Sample Palmprint Images

5. *Conclusion & Future Scope*

This study presents a robust palmprint recognition system that combines the strengths of wavelet-based feature extraction and Convolutional Neural Networks (CNNs). The proposed method explores Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), and Multi-resolution Wavelet Transform (MWT), alongside dimensionality reduction techniques such as PCA and LDA, to enhance classification performance. Experimental results on the PolyU dataset confirm that DWT features, when integrated with LDA and processed through CNN, achieve the highest recognition accuracy. The model demonstrates significant improvements over traditional approaches, particularly in handling variations like illumination, rotation, and alignment errors. This indicates strong potential for real-world deployment in biometric authentication systems requiring high accuracy and reliability. For future work, the system can be expanded to multimodal biometric integration by incorporating palm vein or fingerprint data. Moreover, real-time

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deployment and testing with live acquisition devices can further validate the model's robustness in dynamic environments.

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