Artificial Intelligence Advances | Volume 06 | Issue 01 | October 2023

Artificial Intelligence Advances

https://journals.bilpubgroup.com/index.php/aia

ARTICLE

A Novel Fingerprint Recognition Framework with Attention Mechanism Based on Domain Adaptation for Improving Applicability in Overpressured Situations

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ABSTRACT

Fingerprint recognition is a widely adopted biometric technology, valued for its reliability and precision in identifying individuals. However, traditional recognition methods relying on handcrafted features struggle under challenging scenarios such as overpressured fingerprints, where excessive pressure distorts ridge patterns, significantly affecting performance. To address these challenges, this study proposes a novel framework combining domain adaptation techniques and an attention mechanism. The framework aligns feature distributions between source and target domains, enhancing the model's generalizability to diverse datasets and acquisition conditions. Additionally, the attention mechanism emphasizes critical regions of the fingerprint, improving robustness to distortions. Experimental results demonstrate that the proposed model significantly outperforms the original ResNet, achieving a reduced Equal Error Rate (EER) of 0.0837 compared to 0.1840 for the baseline. Grad-CAM visualizations further validate the model's ability to focus on essential fingerprint features, even under distorted conditions. This study highlights the effectiveness of integrating domain adaptation and attention mechanisms in overcoming real-world challenges in fingerprint recognition.

Keywords: Fingerprint Recognition; Deep Learning; Domain Adaptation

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ARTICLE INFO

Received: 8 September 2024 | Revised: 20 September 2024 | Accepted: 8 October 2024 | Published Online: 25 October 2024

DOI: https://doi.org/10.30564/aia.v6i1.8128

CITATION

Ma, J., Wilson, A., 2024. A Novel Fingerprint Recognition Framework with Attention Mechanism Based on Domain Adaptation for Improving Applicability in Overpressured Situations. Artificial Intelligence Advances. 6(1): 56–65. DOI: https://doi.org/10.30564/aia.v6i1.8128

1. Introduction

Fingerprint recognition is one of the most widely used biometric technologies due to its reliability and accuracy in identifying individuals [1, 2]. The unique patterns of ridges and valleys in fingerprints have made them a standard for personal identification in various applications, ranging from security systems to mobile devices. With its long history and well-established effectiveness, fingerprint recognition has become an integral part of modern life, ensuring secure access control and identity verification.

Traditional fingerprint recognition methods primarily rely on handcrafted features extracted by some traditional models used in many domains [3–5], such as minutiae points, ridge endings, and bifurcations. These features are extracted from the fingerprint image and used to match against stored templates. While these methods have been highly effective in controlled environments with clean and clearly captured fingerprints and other domains [6–8], they often struggle in more challenging scenarios. Factors such as poor image quality, partial fingerprints, and variations in pressure during fingerprint acquisition can significantly degrade their performance. Particularly, overpressured situations—where excessive pressure distorts the fingerprint—pose a considerable challenge for traditional recognition systems, as the distorted patterns may no longer align with the stored templates.

With the rise of artificial intelligence (AI), particularly deep learning [9–11], fingerprint recognition has witnessed a transformative shift. AI-based models, especially those leveraging convolutional neural networks (CNNs) [12–14], have demonstrated remarkable capability in automatically learning robust features from raw fingerprint images. These models have surpassed traditional methods in terms of accuracy and adaptability in many scenarios. However, despite these advancements, the generalizability of AI models remains a concern [15, 16]. AI-based fingerprint recognition systems often struggle when applied across diverse datasets or under varying acquisition conditions. This lack of adaptability limits their practical usability, particularly in environments where the input fingerprints deviate significantly from the data used during model training.

One promising approach to address this limitation is domain adaptation [17, 18], a technique that aims to bridge the gap between different data distributions in machine learning models applied in many tasks [19–21]. For instance, Xiong et al. proposed a domain adaptation-based method for Android malware detection to address the challenge of detecting novel or polymorphic malware that bypasses traditional defenses [17]. By enabling models to adapt to new domains without requiring extensive retraining, domain adaptation can significantly improve the robustness and generalizability of fingerprint recognition systems. It allows the model to align the feature representations of fingerprints from different datasets or acquisition conditions, ensuring consistent performance. Domain adaptation is particularly relevant in scenarios where collecting and labeling large-scale, diverse fingerprint data is impractical or costly.

Overpressured situations represent a common and critical challenge in fingerprint recognition. These situations occur when users apply excessive pressure during fingerprint scanning, leading to distorted patterns that are difficult for models to interpret. Such distortions are not only prevalent but also highly variable, making them a significant obstacle for both traditional and AI-based recognition systems [22–25]. Addressing this issue is crucial for ensuring the reliability and applicability of fingerprint recognition technology in real-world settings, where consistent and precise fingerprint acquisition cannot always be guaranteed.

In response to these challenges, this paper proposes a novel fingerprint recognition framework shown in **Figure 1** designed to enhance the generalizability of models across datasets and improve robustness in overpressured situations. The framework integrates an attention mechanism with domain adaptation techniques to create a more adaptable and resilient recognition system. By leveraging convolutional layers for feature extraction and fully connected layers for classification employed in many studies [26–29], the framework ensures that both global and local fingerprint features are effectively captured. The attention mechanism further refines the feature extraction process by emphasizing the most informative regions of the fingerprint image, which is particularly beneficial for handling distortions caused by overpressured situations. The proposed framework incorporates two key components to enhance its performance. First, a classification loss guides the model to accurately predict the identity of the fingerprint. Second, a distribution alignment loss ensures that the feature representations of fingerprints from different domains are aligned, enabling the model to maintain high accuracy across diverse datasets. These components work in tandem to address the dual challenges of generalizability and robustness, ensuring that the recognition system performs reliably under varying conditions.

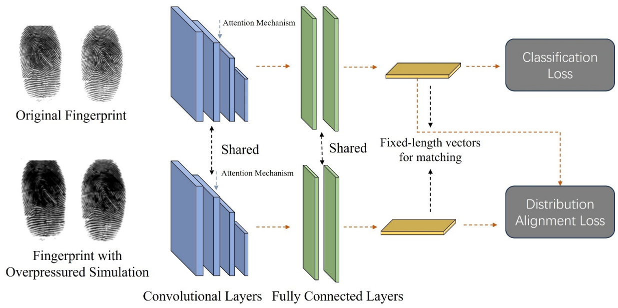

Figure 1. The architecture of the proposed domain adaptation-based fingerprint recognition framework.

2. Literature Review

2.1 Fingerprint Recognition

Deep learning techniques have gained prominence in fingerprint recognition in recent years due to their excellent performance in many domains [30–32]. Drawing inspiration from the human brain's architecture and functionality, these methods enable models to learn intricate patterns effectively. Convolutional Neural Networks (CNNs) have become particularly prominent in computer vision applications [33–35], including biometric identification. Zeng et al. developed a residual network designed to capture local features in fingerprint images [36], improving upon traditional CNN frameworks. Likewise, Althabhawee et al. introduced a deep Convolutional Neural Network (ConvNet) with fifteen layers [37], optimized for fingerprint authentication. Their model includes two distinct stages: the first involves image collection, augmentation, and preprocessing, while the second focuses on feature extraction and matching. The approach demonstrated notable improvements in matching accuracy for fingerprint features.

2.2 Domain Adaptation

Pan et al. categorize transfer learning into three main types based on variations in domains and tasks: inductive, transductive, and unsupervised transfer learning [38]. Inductive transfer learning involves different tasks in the source and target domains, whether or not the domains themselves are the same. This approach often uses annotated data from the source domain but requires some labeled data in the target domain for training. Transductive transfer learning, on the other hand, addresses identical tasks across distinct domains, relying on labeled data from the source domain while utilizing unlabeled data from the target domain during training to estimate its marginal probability distribution. Finally, unsupervised transfer learning, similar to inductive transfer learning in its task and domain variation, operates without labeled data in both source and target domains, using entirely unlabeled datasets instead.

Regarding techniques, domain adaptation can be broadly classified into two categories based on their architectures: shallow and deep. Shallow domain adaptation methods [39–41] often use instance-based and feature-based strategies to align distributions between domains. These strategies typically minimize domain discrepancies using metrics such as maximum mean discrepancy (MMD) [42], Wasserstein distance, correlation alignment (CORAL), Kullback-Leibler (KL) divergence [43], and contrastive domain discrepancy (CDD) [44]. In contrast, deep domain adaptation techniques [45–47] employ neural networks, such as convolutional, autoencoder, or adversarial architectures, to bridge domain gaps. These methods frequently incorporate distance metrics at various layers of dual-network architectures, where one network processes source data and the other processes target data, enabling the comparison of feature representations across corresponding layers to reduce discrepancies.

3. Method

3.1 Dataset Preparation

This study utilized the FVC2004 DB1 fingerprint dataset as the source domain. The FVC2004 competitions are widely recognized as important benchmarks in fingerprint matching research. The dataset consists of 800 images collected from 100 individuals, with each individual contributing 8 impressions. To simulate overpressured situations, the original dataset as the source domain and training dataset was processed by applying contrast enhancements and blurring effects to thicken fingerprint lines, creating a new dataset to serve as the target domain. Overpressured fingerprints were divided, with 20% allocated to the validation set and the remaining 80% to the test set. Sample images from the processed dataset are displayed in **Figure 2**.

Figure 2. The samples of original and preprocessed datasets.

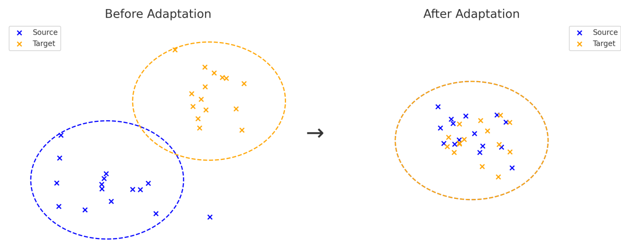

Figure 3. The schematic of the idea related to domain adaptation.

3.2 The Proposed Domain Adaptation-Based Fingerprint Recognition

3.2.1. Preliminaries of Domain Adaptation

Domain adaptation is a subfield of transfer learning that focuses on improving model performance when there is a distributional difference between the source domain (training data) and the target domain (test data). Unlike conventional machine learning methods that assume identical data distributions for training and testing, domain adaptation aims to bridge the gap between differing domains by aligning their feature distributions. This alignment helps models maintain robust performance even when exposed to unseen or diverse data. It is commonly categorized into shallow and deep approaches. Shallow methods rely on statistical techniques, such as minimizing discrepancies using metrics like Kullback-Leibler (KL) divergence, to align source and target domain features. Deep domain adaptation, on the other hand, leverages neural networks to learn transferable features, often incorporating adversarial strategies or dual-network architectures for better domain alignment. This technique is particularly valuable in scenarios where labeled data in the target domain is scarce or unavailable. By utilizing labeled data from the source domain and unlabeled or partially labeled target data, domain adaptation enhances generalizability and reduces the need for extensive data collection and annotation. It is widely applied in tasks like image recognition, natural language processing, and biometric authentication, addressing real-world challenges posed by domain shifts. **Figure 3** provides the schematic of the idea related to the domain adaptation.

3.2.2. MDD-Based ResNet Combined with the Attention Mechanism Framework

ResNet is a widely recognized deep learning architecture known for its ability to train very deep networks effectively by addressing the vanishing gradient problem [48]. Its core innovation lies in the introduction of residual connections, which allow the network to learn residual mappings rather than direct mappings, significantly improving training stability and convergence. ResNet has proven highly effective across various computer vision tasks, including image recognition and biometric authentication.

In this study, we utilize ResNet as the backbone for feature extraction in our fingerprint recognition framework. To further enhance its performance, we integrate the Squeeze-and-Excitation Network (SENet) attention mechanism [49]. SENet introduces a channel-wise attention mechanism by learning to recalibrate the importance of each feature channel. It achieves this through two key operations: squeezing, which captures global information, and excitation, which selectively emphasizes or suppresses channels based on their relevance. By incorporating SENet into ResNet, our model gains the ability to focus on more informative features, improving robustness to distortions such as those found in overpressured fingerprint images.

Following the ResNet-based convolutional layers, we employ fully connected layers for feature transformation. To ensure the alignment of feature distributions between the source and target domains, we introduce the Maximum Disparity Discrepancy (MDD) metric. MDD is a statistical measure used to evaluate the distance between two probability distributions in a reproducing kernel Hilbert space. By minimizing the MDD metric, the extracted features from both domains are aligned, facilitating domain adaptation.

During training, our framework incorporates two loss functions. The first is the classification loss, which ensures the accurate prediction of fingerprint identities. The second is the distribution alignment loss, which minimizes the domain gap by aligning feature distributions. These two loss components work together to optimize the model for both classification accuracy and domain adaptation, resulting in a more generalizable and robust fingerprint recognition system.

3.2.3. Hyperparameter Configuration

This study was implemented using TensorFlow and trained on an NVIDIA 2080 GPU, leveraging its computational capabilities for efficient model training. The Adam optimizer was employed to adjust the model's parameters, taking advantage of its adaptive learning rate and robust performance across various tasks. The training process was conducted 30 epochs with a batch size of 4 to ensure a balance between computational efficiency and model convergence.

To evaluate the model's performance, we utilized the Equal Error Rate (EER) as a key metric [50], alongside the Receiver Operating Characteristic (ROC) curve for a comprehensive analysis. EER is a critical measure in biometric systems, representing the point at which the false acceptance rate (FAR) equals the false rejection rate (FRR). This metric provides a single value to summarize the trade-off between these two error types, making it a valuable indicator of the system's overall reliability. A lower EER corresponds to a more accurate and robust model, highlighting its suitability for practical fingerprint recognition applications. The ROC curve further complements this analysis by visualizing the model's performance across different thresholds, offering insights into its classification capabilities under varying conditions.

4. Experimental Results and Discussion

4.1 The Performance of Fingerprint Matching

In **Figure 4**, the original ResNet model shows a gradual increase in training accuracy, reaching approximately 0.45 by the end of training. However, the validation accuracy remains much lower, peaking around 0.1, indicating significant overfitting. The loss curves reinforce this observation, as the training loss steadily decreases while the validation loss plateaus and fails to improve significantly after a few epochs. This highlights the model as overpressured situations or unseen conditions. The divergence between the training and validation performance suggests that the original ResNet model struggles to adapt to challenging scenarios, leading to suboptimal results on the validation dataset.

Figure 5 illustrates the training curves for the ResNet model enhanced with domain adaptation and attention mechanisms. The training accuracy of this model rapidly increases and stabilizes around 0.85, while the validation accuracy closely follows, stabilizing around 0.8. This demonstrates a substantial improvement in generalization and robustness compared to the original model. The loss curves also show a marked improvement. Although the training loss steadily decreases, the domain adaptation loss (MDD) exhibits an overall decreasing trend, indicating effective domain alignment during training. However, the validation loss shows significant fluctuations in the later stages due to the influence of another MDD loss function. But it still can be observed during the training process, the lowest validation error remains lower than that of the original ResNet, and the optimal weights are selected for the final prediction.

The domain adaptation-based model significantly outperforms the original ResNet model in both training and validation metrics. The inclusion of domain adaptation and attention mechanisms addresses the overfitting observed in the original model by aligning feature distributions between the source and target domains. Additionally, the domain adaptation loss (disc loss) ensures better adaptation to challenging input variations, such as overpressured fingerprints.

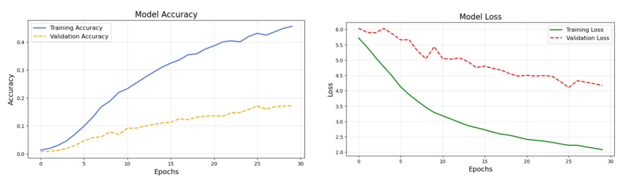

Figure 4. The training curves of the original ResNet model.

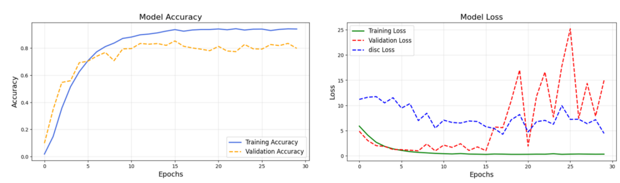

Figure 5. The training curves of the domain adaptation-based ResNet model.

As shown in **Table 1**, the original ResNet model achieves an EER of 0.1840, reflecting its limited capability in balancing the false acceptance rate (FAR) and false rejection rate (FRR). In contrast, the proposed MDD-based ResNet significantly lowers the EER to 0.0837, highlighting its superior ability to minimize errors under challenging conditions such as overpressured fingerprints. This improvement underscores the effectiveness of incorporating domain adaptation and attention mechanisms in enhancing the model's robustness and precision. The ROC curves in Figure 6 provide a visual representation of the models' performance across varying decision thresholds. The original ResNet's ROC curve (left) shows a relatively lower true positive rate (TPR) for given false positive rates (FPR), indicating its suboptimal discriminative power. On the other hand, the ROC curve of the proposed model (right) demonstrates a steeper rise towards the upper-left corner, signifying a higher TPR and better classification performance. The substantial gap between the two curves illustrates the advantage of the proposed model in distinguishing between similar and dissimilar fingerprints.

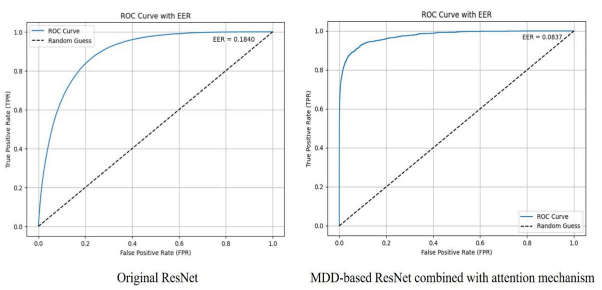

Figure 6. The ROC curves based on various models.

To further visualize the superiority of our proposed model, **Figure 7** presents actual prediction samples under varying conditions, including overpressured simulations. The results compare the cosine similarity values generated by the original ResNet model and the proposed model, highlighting the improvements achieved. For fingerprints belonging to the same identity (left column), the original ResNet model yields a cosine similarity of 0.55, while the proposed model significantly improves this value to 0.88. This demonstrates the enhanced ability of the proposed model to maintain high similarity for distorted fingerprints, even under overpressured conditions. The inclusion of domain adaptation and attention mechanisms enables the model to align features more effectively and focus on critical regions of the fingerprint. In the case of fingerprints from different identities (right column), the original ResNet model produces a cosine similarity of 0.43, which is relatively high and indicates potential misclassification. In contrast, the proposed model reduces this value to 0.18, ensuring a clear separation between fingerprints of different individuals. This highlights the improved discriminative capability of the proposed model.

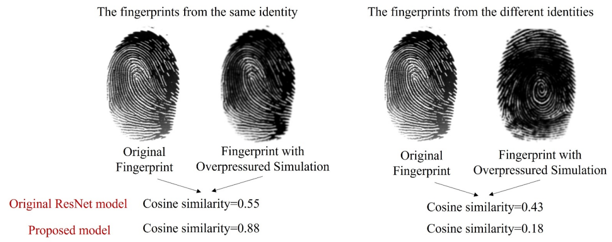

Figure 7. The prediction samples based on various models.

Figure 8 illustrates the average predicted cosine similarity for fingerprints from the same identity and different identities using two models: the original ResNet model and the proposed model enhanced with domain adaptation and attention mechanisms. The original ResNet model achieves an average cosine similarity of 0.55 for fingerprints from the same identity, while the similarity for fingerprints from different identities is 0.32. This indicates moderate performance in distinguishing between identical and non-identical fingerprints. However, the relatively close similarity values suggest limitations in handling challenging fingerprint variations, such as those caused by overpressured situations. In contrast, the proposed model with domain adaptation and attention mechanisms significantly improves performance. For fingerprints from the same identity, the average cosine similarity increases to 0.85, demonstrating better recognition accuracy and robustness. Additionally, the similarity for fingerprints from different identities is reduced to 0.20, indicating a stronger ability to differentiate between distinct fingerprints.

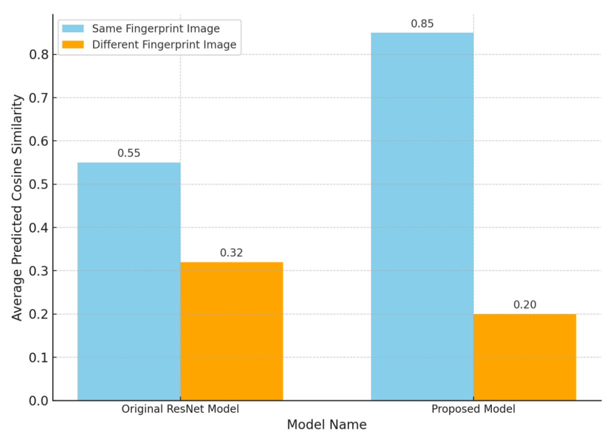

Figure 8. Average predicted cosine similarity by various models.

Table 1. The EER comparison of different models.

Model Name	EER
Original ResNet	0.1840
MDD-based ResNet combined with attention mechanism	0.0837

Figure 9 presents the Grad-CAM visualizations of fingerprints from the same identity, highlighting the attention regions utilized by the proposed model during prediction. The top row corresponds to Identity-1, while the bottom row represents Identity-2. Each pair of images within a row depicts fingerprints of the same individual but captured under different conditions. The visualizations demonstrate that the model consistently focuses on core fingerprint patterns, such as ridges and minutiae, irrespective of variations in the input conditions. Notably, the attention maps show a high concentration of focus in central regions, which are generally more distinct and reliable for fingerprint matching. This consistency across different impressions of the same identity validates the robustness of the model and its ability to generalize to variations in input fingerprints. Furthermore, the Grad-CAM results suggest that the domain adaptation techniques employed in the model successfully mitigate the effects of overpressured situations. By aligning the feature distributions between the source and target domains, the model effectively identifies critical regions for accurate predictions. However, slight differences in the attention distribution between pairs indicate potential areas for improvement in capturing subtle variations, which could further enhance the model's performance in more diverse scenarios.

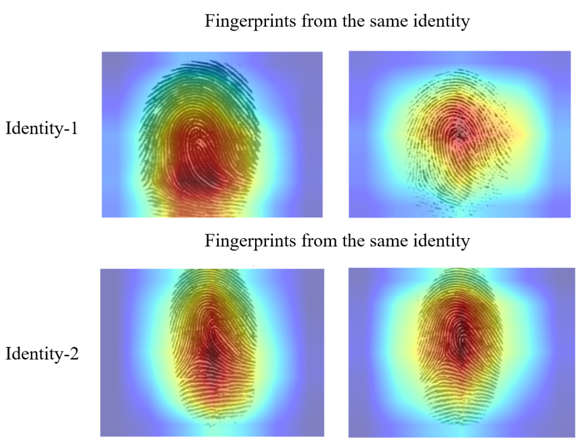

Figure 9. The Grad-CAM visualization of the attention when predicting based on the proposed model.

4.2 Discussion

The proposed domain adaptation approach has demonstrated significant effectiveness in reducing the prediction error of fingerprint recognition models, particularly under challenging overpressured situations. By aligning feature distributions between the source and target domains, the model exhibited improved robustness and generalizability, ensuring reliable performance even when the input fingerprints were distorted due to excessive pressure during acquisition. This improvement underscores the potential of domain adaptation techniques to address real-world challenges where variations in input conditions are inevitable.

Despite these promising results, the approach is not without limitations. First, the domain adaptation process requires access to a representative subset of target domain data, even if unlabeled, to facilitate distribution alignment. In scenarios where such data is unavailable or insufficiently diverse, the model's performance may degrade. Second, the computational cost of domain adaptation techniques, particularly those leveraging deep learning architectures, remains a challenge for deployment in resource-constrained environments. Additionally, while the method successfully mitigates overpressured distortions, it has not been extensively tested across other types of distortions, such as noise, smudges, or partial fingerprints, which are common in real-world applications. Future research should explore strategies to further enhance the adaptability and efficiency of the proposed framework. One promising direction is the integration of self-supervised learning methods to reduce reliance on labeled or even unlabeled target domain data. Additionally, lightweight domain adaptation models could be developed to make the approach more feasible for deployment on edge devices or systems with limited computational resources. Another important avenue for future work is expanding the evaluation of the method to cover a broader range of fingerprint distortions and datasets, ensuring its applicability across diverse real-world scenarios.

5. Conclusion

This study introduces a robust fingerprint recognition framework that leverages domain adaptation and attention mechanisms to address challenges in overpressured fingerprint scenarios. The proposed model significantly improves accuracy and generalizability, as evidenced by its lower EER and better performance on unseen data. The domain adaptation technique effectively aligns feature distributions, while the attention mechanism enhances feature extraction by focusing on critical fingerprint regions. Despite these advancements, the approach has limitations, including reliance on target domain data and computational complexity. Future research should focus on developing lightweight models and expanding the framework's applicability to other fingerprint distortions such as noise and partial images. By addressing these challenges, this framework offers a promising solution for building reliable and adaptable fingerprint recognition systems suitable for diverse real-world applications.

Author Contributions

J.M. is responsible for the conceptualization, designing and implementation of the fingerprint recognition framework as well as the drafting of the manuscript. A.W. is responsible for data collection, preprocessing and manuscript revision.

Funding

This research received no external funding.

Data Availability Statement

Not applicable.

Conflict of Interest

Declaration of conflict of interest.

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