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Article

Fingerprint Image Generation Based on Attention-Based Deep Generative Adversarial Networks and Its Application in Deep Siamese Matching Model Security Validation

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Abstract: This study addresses the critical need to evaluate the security of deep learning models in fingerprint recognition systems, by testing their vulnerability to misidentification. While deep learning techniques have significantly advanced biometric authentication, the potential for misclassification and unauthorized access due to synthetic fingerprints has not been thoroughly investigated. To this end, we propose an enhanced Deep Convolutional Generative Adversarial Network (DCGAN) with attention mechanisms to generate realistic synthetic fingerprint images. These images are then used to test the robustness and security of a Siamese Network employed for fingerprint matching. Experimental results demonstrate that the AE-DCGAN model outperforms traditional DCGANs in image quality and precision, achieving higher accuracy in generating realistic fingerprint textures. Additionally, the Siamese Network, when tested with synthetic fingerprints, reveals certain vulnerabilities, highlighting potential risks in security. Grad-CAM visualizations are employed to further understand the model's attention during fingerprint matching, providing insights into how the model focuses on key fingerprint features. The proposed approach aims to investigate both the generation and recognition phases, contributing to improved robustness and reliability in fingerprint-based systems.

Keywords: component; DCGAN; fingerprint generation; attention mechanism; Siamese Network

Introduction

Biometric authentication, which identifies individuals by quantitatively analyzing physical and behavioral traits, has become a cornerstone of identity verification and access control in computer science. Among various biometric techniques, fingerprint recognition stands out due to its unique features, stability, and ease of acquisition, making it a reliable and extensively used method. Applications of fingerprint recognition span diverse fields, including law enforcement, access control systems, and financial transactions. Its distinctive and enduring nature also makes fingerprints invaluable in forensic science and criminal investigations.

Recently, deep learning techniques [1–3], such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been applied to enhance fingerprint recognition systems. However, the limited availability of diverse and large-scale publicly accessible datasets has hindered progress in developing and

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evaluating current machine learning or deep learning models [4–6]. Furthermore, insufficient attention has been paid to the security vulnerabilities of deep learning-based fingerprint systems, leaving them susceptible to adversarial attacks that could lead to incorrect recognition or unauthorized access.

Earlier fingerprint recognition methods primarily relied on digital image processing, focusing on the extraction of minutiae points—distinctive features such as ridge endings and bifurcations. Significant research, such as the work by Jain *et al.*, combined minutiae points with texture information to improve matching accuracy, demonstrating promising results [7]. However, minutiae extraction faced challenges when processing low-quality fingerprint images. To overcome these issues and further improve recognition performance, deep learning algorithms have increasingly been employed due to their superior capabilities in computer vision tasks [8–11]. For instance, Engelsma *et al.* developed DeepPrint, a CNN-based method that achieved a Rank-1 accuracy of 97.9% on the NIST SD4 dataset [12]. Similarly, Cao *et al*. introduced a deep neural network for latent fingerprint search with successful results [13]. Despite these advancements, privacy concerns often restrict the availability of comprehensive public fingerprint datasets, limiting the potential of these algorithms [14]. This highlights the necessity for generating diverse and high-quality fingerprint datasets to improve training and evaluation processes. Fingerprint generation techniques can address this need by creating synthetic fingerprints to enhance model performance. Cappelli, for instance, proposed a method using directional image modeling to generate realistic fingerprint images [15]. Recently, deep learning models have also been utilized for fingerprint synthesis due to their excellent performance in various domains [16–19]. Engelsma *et al*. introduced a deep generator capable of producing realistic synthetic fingerprints, accompanied by a publicly available dataset [20]. However, while research has explored fingerprint generation and matching, the security implications of using synthetic fingerprints to compromise recognition systems remain underexplored. To address these challenges, this study proposes an enhanced Deep Convolutional Generative Adversarial Network (DCGAN) incorporating attention mechanisms to generate realistic fingerprint images shown in Figure 1 [21] . Furthermore, it constructs a Siamese Network used for fingerprint matching and evaluates its robustness against security threats by leveraging the synthetic fingerprints generated by the DCGAN model [22].

This paper is organized as follows: Section 2 reviews related works in fingerprint recognition and generation. Section 3 outlines the workflow of the proposed method. Experimental results and their analysis are presented in Section 4. Lastly, Section 5 concludes the paper with a summary of findings.

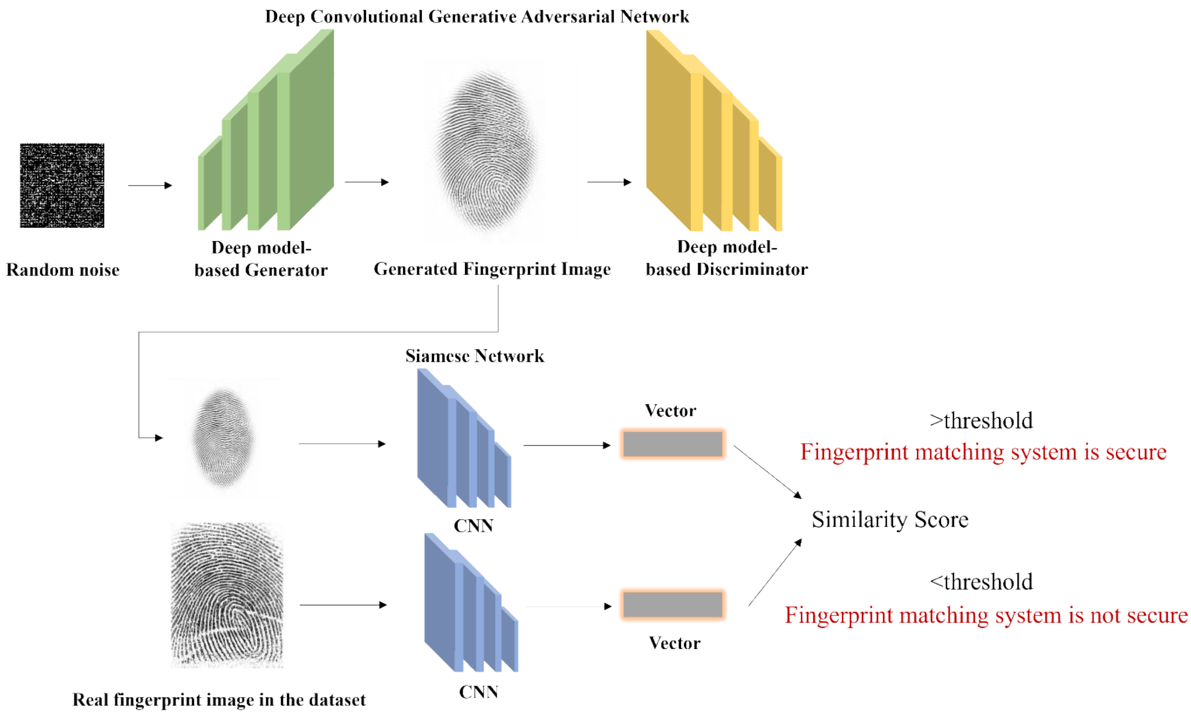


Figure 1. The procedure of the proposed framework in terms of fingerprint generation and security verification based on deep learning models.

2. Literature Review

2.1. Fingerprint Recognition

Deep learning algorithms have emerged as a highly effective approach for fingerprint recognition in recent years [23–26]. These algorithms are inspired by the architecture and functionality of the human brain, enabling the development of models capable of learning complex patterns. Among these models, Convolutional Neural Networks (CNNs) have gained significant popularity in computer vision tasks, including biometric recognition. Recent advancements in fingerprint recognition research have further leveraged the capabilities of CNNs and ViTs. For example, Zeng *et al*. introduced a residual network to extract local features from fingerprint images, enhancing the conventional CNN structure [27]. Qiu *et al*. proposed a multi-stage interpretable fingerprint matching network, IFViT, leveraging Vision Transformers (ViT) to enhance pixel-level correspondence, global context understanding, and the interpretability of fixed-length fingerprint representations [28]. Similarly, Althabhawee *et al*. proposed an efficient fingerprint authentication model utilizing a deep Convolutional Neural Network (ConvNet) comprising fifteen layers [29]. The model operates in two stages: a preparation stage, which includes image collection, augmentation, and preprocessing, and a second stage focused on feature extraction and matching. The results demonstrated that this approach delivered superior matching performance for the given fingerprint features.

2.2. Fingerprint Generation

In the realm of fingerprint generation, deep learning models have shown potential due to their excellent performance from other domains [30–33], similar to their applications in fingerprint matching. For example, Xiong *et al.* proposed employing Distributed Data Parallel (DDP) frameworks to efficiently scale the training of deep learning models for synthetic fingerprint generation, enhancing training efficiency, data security, and managing large datasets while addressing GPU underutilization challenges [34]. Fahim *et al*. used a combination of residual networks and spectral normalization to create fingerprints [35]. Their method, featuring average residual connections, was more effective in preventing vanishing gradients compared to traditional residual connections. Spectral normalization helped stabilize weight variation within the network. They also used the Multi-scale Structural Similarity (MS-SSIM) metric to evaluate the diversity of the generated samples, indicating that their approach could produce a varied set of images while reducing the risk of mode collapse. Minaee *et al.* developed a machine learning framework based on Generative Adversarial Networks (GANs), enhancing it with a specific regularization term in the loss function. The model's performance was measured using the Frechet Inception Distance (FID), showing significant quantitative improvements [36].

3. Method

3.1. DCGAN-Based Fingerprint Generation

The effectiveness of deep learning models has been widely demonstrated [37–39]. Thereinto, generative adversarial networks are a type of deep learning model designed to produce synthetic data that closely mimics a given dataset. They consist of two neural networks: the generator and the discriminator, as illustrated in Figure 2. The generator starts with random noise as input and creates new data samples, while the discriminator evaluates both real and generated data, classifying them as authentic or synthetic. During training, the generator aims to produce data that can convincingly deceive the discriminator, while the discriminator continuously improves its ability to distinguish real data from fake. This adversarial training process pushes the generator to create increasingly realistic data as it refines its ability to replicate the characteristics of genuine data. The discriminator, in turn, becomes more adept at identifying synthetic samples. Over time, this dynamic leads to the generation of highly realistic data, making GANs useful for various applications, including image synthesis, music composition, and natural language processing.

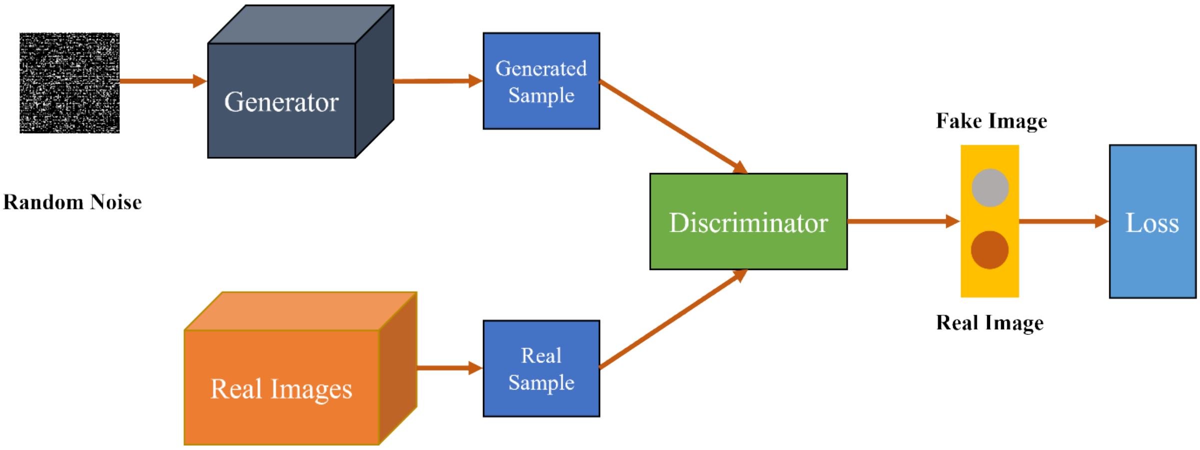


Figure 2. The structure of the GAN.

However, GANs face several well-documented challenges, including unstable training dynamics, mode collapse, and difficulty in generating high-quality outputs. Unstable training often arises due to the adversarial nature of GANs, where the generator and discriminator simultaneously compete to optimize opposing objectives, sometimes leading to oscillations or divergence. Mode collapse occurs when the generator produces a limited variety of outputs, failing to capture the diversity present in the training data. Additionally, GANs struggle with generating high-resolution images, as traditional GAN architectures are often inadequate for capturing detailed spatial information or complex patterns in data.

To address the traditional challenges of GANs, Deep Convolutional GANs (DCGANs) were introduced as a specialized GAN variant that incorporates deep convolutional neural networks for both the generator and discriminator. DCGANs offer several improvements: (1) Enhanced stability: By adhering to specific architectural principles, such as batch normalization and the exclusion of fully connected layers, DCGANs achieve more stable training dynamics compared to traditional GANs. (2) Improved image generation: The use of convolutional layers enables DCGANs to better capture spatial information, leading to higher-quality and more realistic image generation. (3) Greater scalability: DCGANs are capable of handling larger and more complex datasets, making them suitable for a wider range of applications.

3.2. The Introduction of Attention Mechanisms in SENet

In this study, the Squeeze-and-Excitation (SE) block is incorporated into the proposed DCGAN to enhance the realism of generated fingerprint images. Introduced by Hu *et al.* in 2017 [40], the Squeeze-and-Excitation Network (SENet) is a deep learning architecture designed to recalibrate channel-wise feature responses adaptively by modeling interdependencies among channels. This is achieved through the SE block, a lightweight gating mechanism that integrates seamlessly into various CNN architectures.

The SE block introduces a novel attention mechanism to amplify the representational power of CNNs by selectively emphasizing critical channels and suppressing irrelevant ones. It operates through two key steps: squeeze, which captures global channel dependencies, and excitation, which recalibrates the channel responses. These recalibrated features are then used to refine the output in subsequent layers. Building upon this attention mechanism, this study integrates the SE block into the generator of the GAN framework to improve the quality of generated fingerprint images. By incorporating the SE block, the generator can prioritize key features, such as minutiae points or pore details, that are crucial for fingerprint representation. This selective focus enhances the generator's ability to produce high-quality images by adaptively weighting important regions or features within the input data. The attention mechanism allows the generator to assign varying levels of importance to different spatial regions, enabling it to capture intricate details and spatial relationships more effectively. As a result, the generated fingerprint images exhibit greater realism and finer detail, closely resembling authentic data. Conversely, this study does not apply the attention mechanism to the discriminator. This decision is based on the discriminator's inherent ability to distinguish real from synthetic data, which is less critical for improving the realism of the generated images. Instead, the emphasis is placed on refining the generator's capacity to produce realistic outputs. By focusing the attention mechanism on the generator, the proposed framework effectively enhances the quality of fingerprint generation, achieving the primary objective of this study.

3.3. The Introduction of Siamese Network

Siamese networks are a class of neural networks designed for tasks that require similarity comparison between two inputs, such as image matching, signature verification, and biometric authentication [41]. Unlike traditional neural networks, which predict class labels or regression values, Siamese networks output a similarity score that quantifies the relationship between two inputs. The architecture consists of two identical subnetworks that share the same parameters, ensuring that both inputs are processed symmetrically and comparably. Each subnetwork in a Siamese architecture extracts features from one of the inputs. These features are then passed to a similarity function, such as the Euclidean distance or cosine similarity, to compute the relationship between the two inputs. The shared weights enable the network to learn invariant feature representations, making it robust to variations such as orientation, scale, and noise in the input data. Siamese networks are particularly effective in scenarios with limited labeled data. By learning to compare pairs of inputs rather than classify individual instances, they significantly expand the dataset through the creation of multiple input pairs. This characteristic makes them ideal for applications in biometrics, where labeled data is often scarce.

In this study, fingerprint images generated by the proposed method are sequentially introduced into the Siamese network to simulate an attack scenario, matching them against an existing fingerprint database. This evaluation assesses the security of the proposed network and its susceptibility to compromise by synthetic fingerprints. The primary similarity metric used is the Euclidean distance. If the similarity score between a generated fingerprint and an authentic fingerprint in the database falls below a predefined threshold, a false match is recorded, highlighting the system's potential security vulnerabilities and the need for further refinement.

The proposed Siamese network leverages the VGG and MobileNet models as its backbone architectures [42,43]. VGG, developed by the Visual Geometry Group at the University of Oxford, is a deep CNN designed for image recognition and classification tasks. Notable for its success in the 2014 ILSVRC, VGG employs small 3×3 convolutional filters stacked in multiple layers, with variants such as VGG-16 and VGG-19. However, its high computational demands limit its practicality in mobile or real-time applications. In contrast, MobileNet, developed by Google, is a lightweight CNN architecture optimized for mobile and embedded vision applications. MobileNet achieves a balance between computational efficiency and accuracy by using depthwise separable convolutions, which significantly reduce the number of parameters and computational cost without compromising performance. With options for different width multipliers and resolutions, MobileNet offers flexibility to meet various computational and memory constraints, making it well-suited for resource-constrained environments.

4. Experimental Results and Discussion

4.1. Datasets Description

The FVC2002 and FVC2004 competitions serve as notable benchmarks in fingerprint matching research, providing access to eight fingerprint databases. Each database contains 800 fingerprint images obtained from 100 distinct individuals. For this study, only genuine fingerprint databases were utilized, specifically FVC2002 DB1, DB2, and DB3, along with FVC2004 DB1, DB2, and DB3. Synthetic fingerprint databases, such as FVC2002 DB4 and FVC2004 DB4, were excluded from the analysis. Consequently, the dataset employed in this study comprises 4800 fingerprint images sourced from six databases. Sample images from the collected dataset are shown in Figure 3.

Figure 3. The sample images used in this study.

4.2. The Performance of Fingerprint Generation

The first row of Figure 4 illustrates fingerprint images generated by the conventional DCGAN model, while the second row displays those produced by the proposed AE-DCGAN model. Experimental results indicate that as training iterations increase, the quality of fingerprint images generated by both models improves progressively. Initially, at epoch 0, the generated images appear as grid-like patterns, as the untrained models simply map input 1-D noise into 2-D images without meaningful features. However, by epoch 10, both models begin to capture basic fingerprint textures, such as their approximate shape, from the FVC dataset. At epoch 500, the AE-DCGAN model significantly outperforms the conventional DCGAN, producing fingerprint images with high precision, whereas the DCGAN model captures only a rudimentary contour.

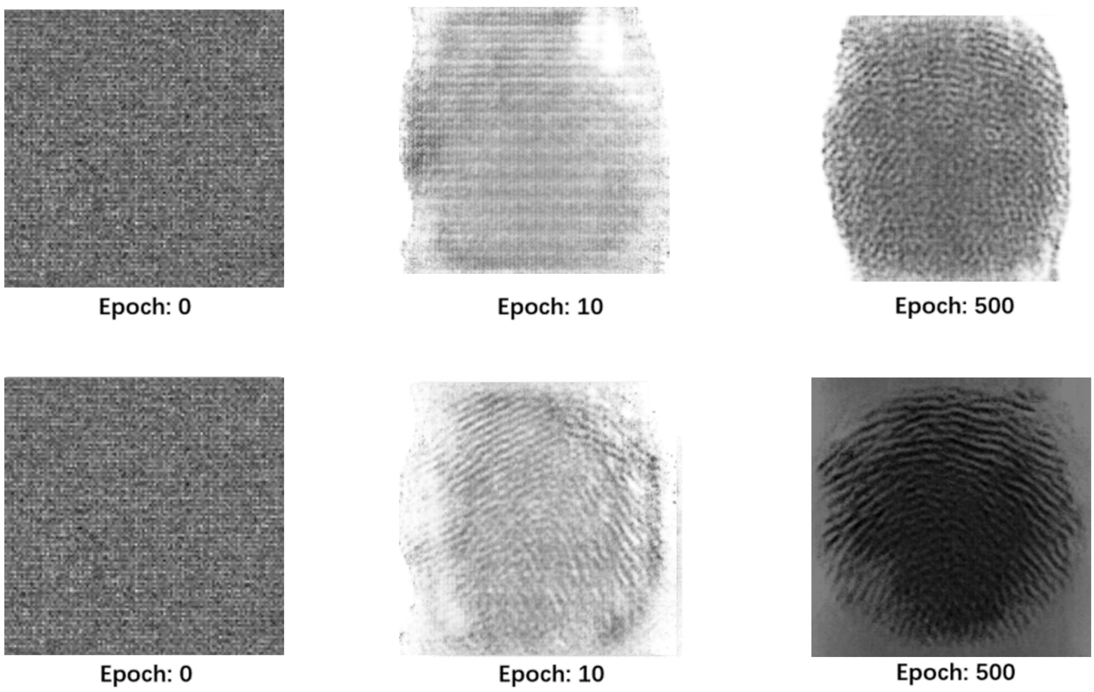
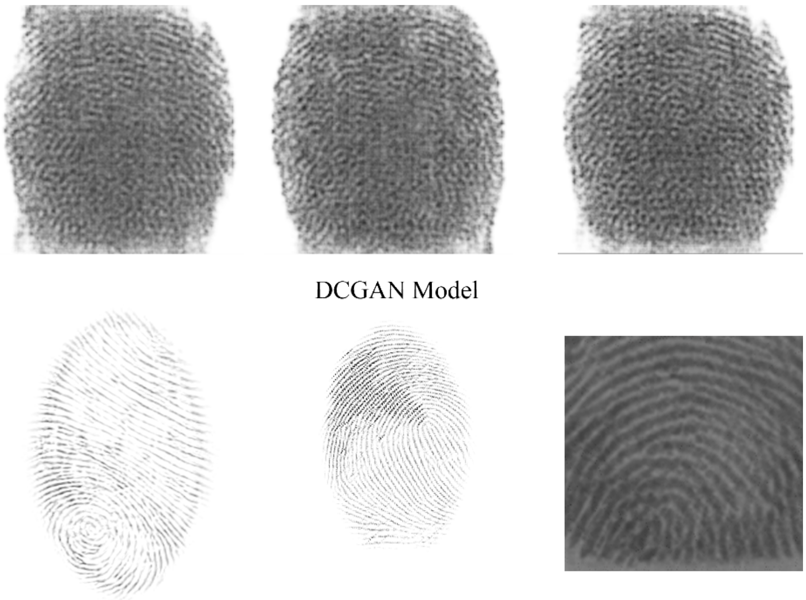


Figure 4. The visualization of generated fingerprint images during different stages.

Additionally, the AE-DCGAN model demonstrates faster learning of fingerprint textures, including shape and structure, in the early training stages compared to the DCGAN model. This highlights the superior generative performance of the AE-DCGAN model. Figure 5 further showcases additional cases, revealing that the DCGAN-generated fingerprints often lack coherence in texture and exhibit local omissions, while the AE-DCGAN-generated fingerprints display more consistent texture, better clarity, and no missing regions.

Several factors contribute to the success of the AE-DCGAN model in this study: (1) Incorporation of attention mechanisms: The attention mechanism allows the AE-DCGAN generator to prioritize key fingerprint components, such as minutiae and ridges, during training. This focus is evident in the enhanced fingerprint details shown in Figures 4 and 5. In contrast, the conventional DCGAN fails to capture these critical features, resulting in chaotic ridge patterns. (2) Reduction of missing regions: The AE-DCGAN model effectively allocates attention to essential features, preserving complete fingerprint ridge structures. In comparison, the DCGAN model often misinterprets irrelevant background noise, such as white spaces, as meaningful features, leading to local area omissions in the generated images. However, in some instances, the AE-DCGAN model may also produce fingerprint images with blurred and inconsistent textures, as shown in Figure 6. However, these cases are relatively rare and do not significantly impact the overall performance of the model.



DCGAN Model

AE-DCGAN Model

Figure 5. More examples generated from DCGAN and AE-DCGAN model.

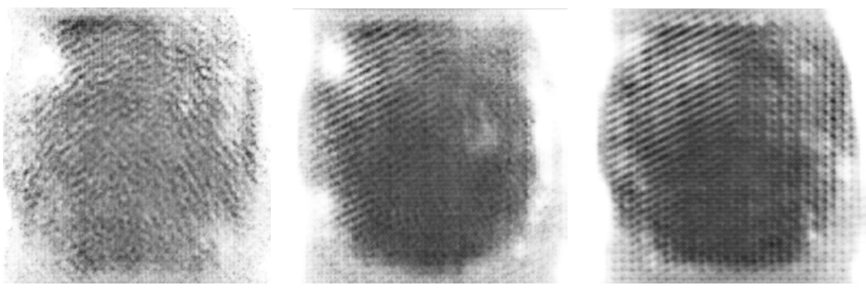


Figure 6. Failure examples generated from the AE-DCGAN model.

4.3. The Performance of Fingerprint Matching

Figure 7 showcases the performance of two classical convolutional neural networks in evaluating identical and distinct fingerprint pairs within the test set. Ideally, an effective model should yield low Euclidean distance scores for identical fingerprint pairs, indicating high similarity, and higher scores for distinct pairs, signifying low similarity. According to the results, the MobileNet model achieves an average Euclidean distance of 0.93 for identical fingerprint pairs and 1.25 for distinct pairs. In contrast, the VGG model records 0.38 for identical pairs and 7.77 for distinct pairs. Notably, the VGG model outperforms MobileNet, demonstrating its superior discriminative and predictive capabilities in fingerprint matching tasks.

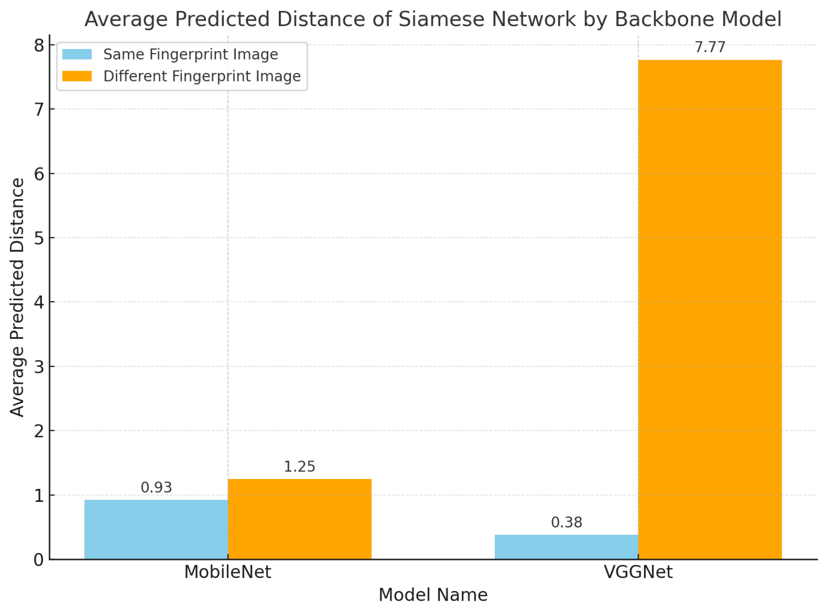


Figure 7. Average predicted distance of Siamese network by backbone model.

The superior performance of the VGG model can largely be attributed to its greater number of parameters, enabling it to capture and learn more intricate features from images [44,45]. While MobileNet relies on depthwise convolutions and is optimized for resource-constrained environments, such as mobile devices [46], its reduced parameter count limits its ability to handle complex feature-rich datasets like fingerprints. In comparison, the parameter-rich VGG model is better suited for tasks requiring detailed feature extraction, leading to enhanced performance in fingerprint recognition.

Furthermore, this study also evaluates the reliability and security of Siamese networks in fingerprint matching by testing generated fingerprint images against genuine ones stored in the database. The trained VGG-based Siamese network is utilized for prediction, and two illustrative cases are provided in Figure 8. In these examples, the left fingerprint images are generated by the AE-DCGAN model, while the right images are from the FVC dataset. In the first case, the Siamese network assigns a Euclidean distance of 0.021, significantly lower than the average similarity score of 0.38 observed earlier. This erroneously identifies the fingerprints as belonging to the same individual. Similarly, in the second case, the generated and real fingerprints receive a distance score of 0.032, leading to another incorrect match. These results indicate that the trained Siamese network carries certain security and reliability risks when handling generated fingerprint images, underscoring the need for further refinement to improve its robustness and resilience against adversarial scenarios.

Figure 9 further illustrates the Grad-CAM visualization of the attention areas during the fingerprint matching prediction process [47–49]. The heatmaps highlight the regions that the matching model focuses on when making predictions. The red areas indicate regions of high attention, while the blue areas indicate regions of lower attention. The visualization clearly shows that the model concentrates on specific fingerprint features, such as ridges and minutiae points, during the matching process. This suggests that the model is effectively learning to focus on the most distinguishing features for comparison. The use of Grad-CAM provides an intuitive understanding of the model's behavior and helps verify that the model is focusing on meaningful fingerprint regions, thereby improving the interpretability of the matching results.

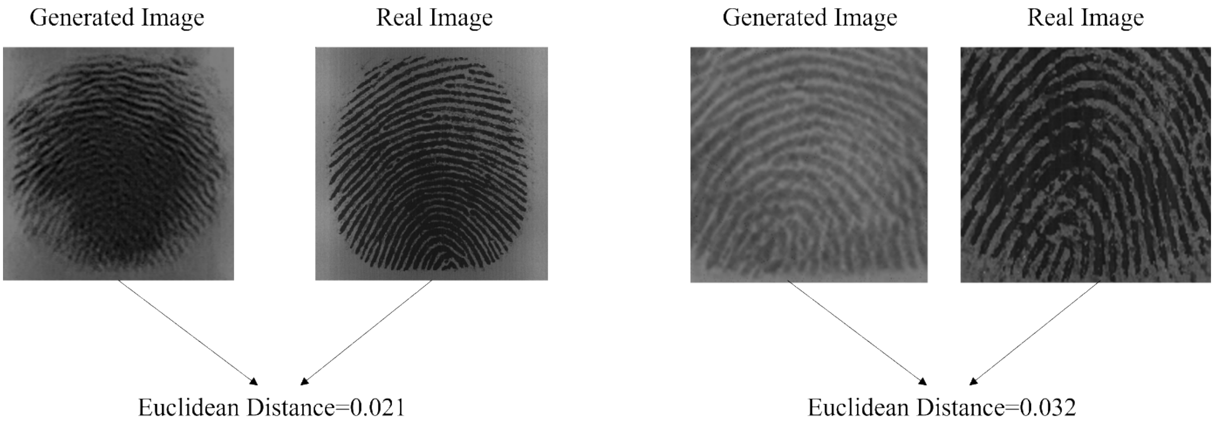


Figure 8. Predicted results using generated and genuine fingerprint image inputs.

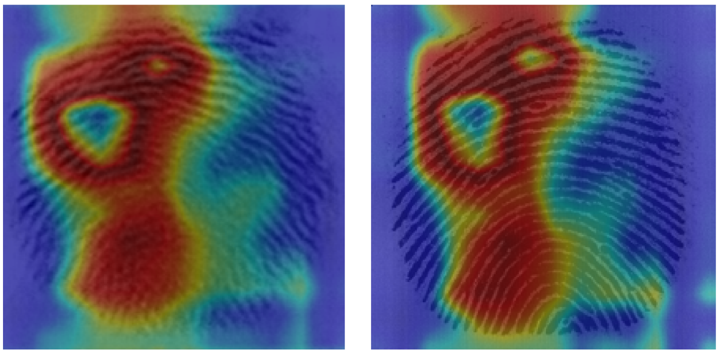


Figure 9. The Grad-CAM visualization of the attention when predicting.

4.4. Discussion

This study explores the potential of deep learning models for fingerprint generation and matching, demonstrating notable advancements but also revealing several limitations and areas for future improvement. The use of genuine fingerprint datasets from FVC2002 and FVC2004 competitions provides a strong benchmark for evaluating model performance. However, the exclusion of synthetic datasets, such as FVC2002 DB4 and FVC2004 DB4, limits the diversity of the data and potentially restricts the generalizability of the findings. Expanding the dataset to include synthetic and real-world fingerprints from various populations and environments would enhance the robustness of the proposed models. The AE-DCGAN model shows significant improvements in generating high-quality fingerprint images compared to conventional DCGAN. It effectively learns ridge structures and minutiae while reducing local omissions. Nonetheless, limitations remain, as some generated images exhibit blurred and inconsistent textures. These issues, while infrequent, indicate that the model may still struggle with capturing finer details, such as pores, in certain cases. Advanced generative architectures, such as transformer-based models or diffusion models, could be explored to further improve the quality and coherence of generated fingerprints. Additionally, optimizing the training process to better handle these inconsistencies would contribute to more reliable outputs. The VGG-based Siamese network demonstrates superior performance in fingerprint matching compared to MobileNet, particularly in identifying identical and distinct fingerprint pairs. However, there are notable risks associated with matching generated fingerprints. As shown in Figure 8, the network occasionally misclassifies generated fingerprints as genuine, assigning low Euclidean distances and resulting in false matches. This highlights potential security vulnerabilities, especially in adversarial scenarios where generated fingerprints might be exploited to spoof authentication systems. Addressing these risks through adversarial training, feature regularization, or mechanisms to distinguish between genuine and generated fingerprints is critical to enhancing the model's reliability. In addition, some advanced methods from other domains can be also considered for further improving the performance of models.

5. Conclusion

This study demonstrates the effectiveness of using an enhanced DCGAN with attention mechanisms for generating high-quality fingerprint images and employing a Siamese Network for matching. The AE-DCGAN model achieves superior generative performance compared to conventional DCGANs, producing clearer and more consistent fingerprint textures. However, the security evaluation reveals that the Siamese Network is susceptible to misidentifying synthetic fingerprints as genuine, exposing vulnerabilities in deep learning-based fingerprint recognition systems and indicating the need for further refinement to improve model robustness. Grad-CAM visualizations provide valuable insights into the model's focus during fingerprint matching, emphasizing the importance of interpretability in enhancing system security and reliability. Future work will focus on improving the discriminator's robustness, incorporating more diverse datasets, and exploring advanced attention mechanisms to further enhance the model's performance and security against adversarial threats.

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Conflicts of Interest

The authors declare no conflict of interest.

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