

Advancements in Latent Fingerprint Enhancement Techniques for Precise Minutiae Detection: A Review

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Abstract:

Considered as a focal point in forensic science, the identification of latent fingerprints is based on various factors such as nature of noise, contrast, and partial impressions. This study covers the evolution processes behind fingerprint enhancement techniques, focusing on hybrid deep learning models utilizing CNN and ViT, along with the attention mechanism, to perform direct crime scene-enhanced minutiae extraction. Conventional approaches and rule-based AFIS struggle with latent print quality variations. Recent methodological advances include extraction of global and local features, image data augmentation, and attention-guided concentration of classification efforts, all yielding robust classification across variable fingerprint conditions. The paper also conducts an analysis of enhancement methods, models, and datasets, and serves as a roadmap to building robust and scalable fingerprint identification solutions for operational forensic use.

Keywords: Latent Fingerprint, Minutiae Detection, Deep Learning, CNN-ViT Hybrid, Attention Mechanism, Biometric Recognition

I. INTRODUCTION

Fingerprint recognition has long been established as a core biometric mode due to its uniqueness, permanency, and reliability in establishing identity. It is vital to forensic investigations, border protection, and control systems for entry. Usually, fingerprint lands captured under controlled environments tend to be very fine in either rolled or plain impressions. On the other hand, the challenge becomes absolutely magnified when such impressions are latent fingerprints-the very left-behind crime scene. These impressions are usually incomplete, noisy, smudged, and skewed, making it all the more difficult for conventional fingerprint recognition systems to extract minutiae points and match them with any degree of reliability.

Fingerprint recognition systems like the AFIS rely mainly on hand-crafted features, which consist mostly of minutiae points such as ridge endings and bifurcations. In contrast, such systems are hardly able to successfully operate on low-quality features or those having partial prints. Further complicating this is the degradation of the ridge-valley contrast, with other factors such as background noise and environmental effects degrading the latent print quality. Traditional filters such as Gabor filters, FFTs, and histogram equalizations have been applied for image enhancement and restoration, but are proven almost always last when a print is corrupted beyond place.

Deep learning is revitalizing developments in latent fingerprint enhancement and minutiae detection. CNNs are great at extracting local features such as ridge structures and pores; however, ViTs can model long-range dependencies and capture contextual information at a global scale. Each approach brings its own set of advantages, while also posing its own drawbacks. CNNs have limited receptive fields and weakly handle global relationships, while ViTs mostly require huge datasets and fall short in fine-grained spatial precision when applied alone.

The study addresses latent fingerprint enhancement approaches, especially dealing with hybrid deep learning frameworks for the accurate detection of minutiae. The article aims at discussing the pros and cons of traditional and contemporary approaches, highlighting advancements that have appeared in model architecture, and addressing the challenge of datasets. In conclusion, it proposes an organization of the current state-of-the-art approaches and offers perspectives for the future development of scalable, real-time, and forensic-grade fingerprint recognition systems. Fig. 1 describes enhancing fingerprint matching with deep learning.

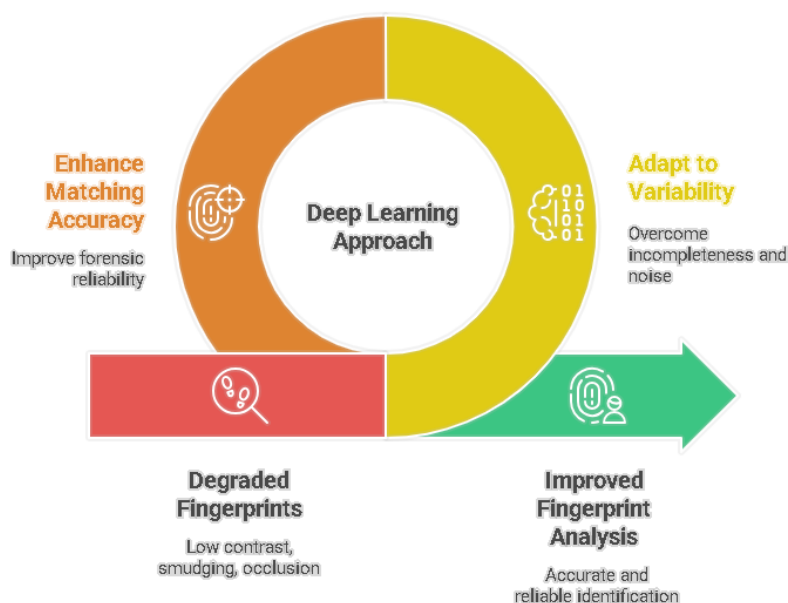


Fig. 1: Enhancing Fingerprint Matching with Deep Learning

A. Deep Learning in Fingerprint Recognition

Deep learning has revolutionized fingerprint recognition by providing powerful methods for modelling intricate fingerprint patterns and structures. Contrary to traditional algorithms wherein features are handcrafted, features here are discriminatively learned by deep neural networks from the raw input data [18]. CNNs are good at capturing local spatial information, such as ridge structures and minutiae, useful in high-resolution fingerprint classification. CNNs, however, may have limitation in grasping long-range dependencies and global contexts, especially for partial or latent prints. ViTs, conversely, build global relations using self-attention mechanisms, allowing for comprehension of the fingerprint topology in a more holistic manner. Coupled with attention modules, these models learn to weigh relevant regions dynamically, thus improving classification performance [19]. Fig .2 describes deep learning in fingerprint recognition.

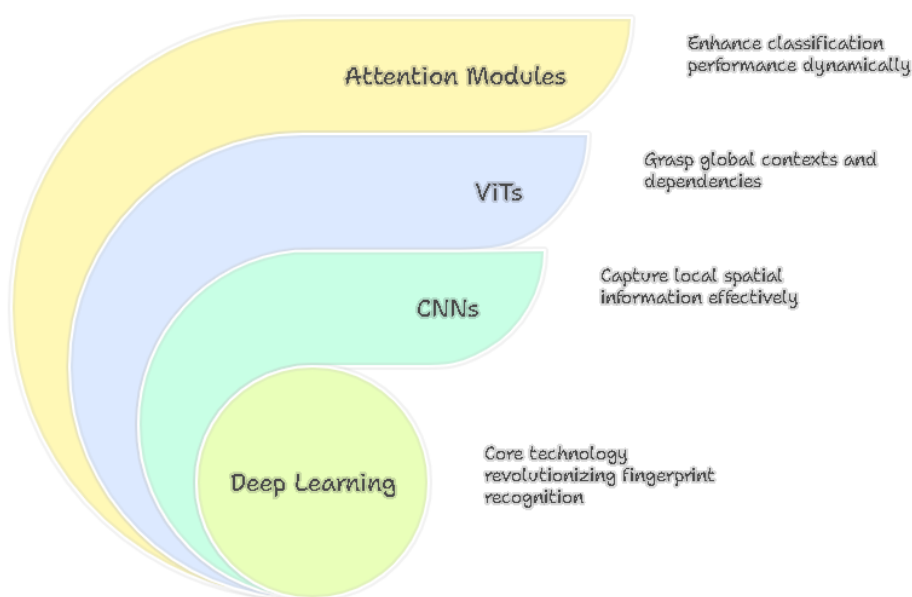


Fig .2: Deep Learning in Fingerprint Recognition

II. LITERATURE REVIEW

Abdul Wahab et al. [1] (2024) uses a GAN-based enhancement technique that integrates information about minutiae location and orientation fields to best enhance latent fingerprint clarity and ridge preservation. It is computationally expensive and very hard to balance the realism of the fingerprint with accurate feature preservation.

Temirlan Meiramkhanov et al. [2] (2024) Combined CNNs with Gabor filter enhancement techniques to improve recognition accuracy on manipulated fingerprint impressions to 94% with the Sokoto Coventry dataset. Low generalization capacity across different fingerprint kinds; heavy reliance on dataset-specific tuning.

Milind B. Bhilavade et al. [3] (2024) Compared matching scores for relatively poor fingerprint images reconstructed by conventional minutiae-based methods and deep learning, varying between 23–94% (DL) and 82–99.99% (minutiae-based). Deep learning methods performed inconsistently with different types of damage and considering the image quality.

Hongtian Zhao et al. [4] (2024) ResNet with Generalized IoU-based NMS for outlier-resistant minutiae extraction, outperforming state-of-the-art methods over the NIST SD4 and FVC2004 datasets. The performance depends on inference accuracy, with very large annotated datasets.

Sahar A. El Rahman et al. [5] (2024) Presented CNN-based fingerprint unimodal and ECG-fingerprint multimodal systems, the sequential fusion ones yielding the highest AUC (0.99). High complexity in managing multimodal data and training large-scale fusion models.

A. A. Mulay et al. [6] (2024) Used ensemble of minutiae configurations with U-Net and ViT, gaining around 1.7% higher accuracy on challenging datasets such as NIST SD302. Slight performance gains with increased model complexity via ensemble strategies.

T. Kavitha et al. [7] (2024) Comprises an automated fingerprint recognition system for forensic crime detection with CNNs, having an accuracy exceeding 81%. Limited performance due to small data size and availability of better preprocessing techniques for noisy inputs.

P. Khare et al. [9] (2024) Introduced YOLO-based fingerprint recognition models trained on 4,000 annotated images, which raised mAP@0.5 from 93% to 97.4%. Accuracy depends heavily on annotated data quality; due to small datasets, it is difficult to generalize well.

Zexi Jia et al. [9] (2024) Finger Recovery Transformer (FingerRT) is designed to restore degraded or partial prints by harnessing the powers of Vision Transformers and enhancement networks. More computationally expensive and sensitive to segmentation errors during preprocessing.

S. Kriangkajorn et al. [10] (2024) A frequency-domain latent print restoration framework using deep learning filter predictors was proposed to increase rank-1 identification accuracy. Complicated block partition; performance degrades strongly with the initial filter quality and level of degradation.

Z. Pan et al. [11] (2024) Dense Minutia Descriptor was developed by using deep learning concepts to encode 3D minutiae patches for precise latent matching. One limitation involved being exhaustive and computationally expensive during matching, while also having difficulties with overlapping and noisy backgrounds.

N. Bhargava et al. [12] (2024) Employed image processing followed by skeletonization in order to form bit-string-encoded fingers for easy storage and matching. It is not robust to heavy noise and may discriminate against partial and distorted inputs.

R. Bano et al. [13] (2024) Approach to AFIS classification proposed by deep learning using features such as hand orientation and sweat pore patterns. The approach is far too dependent on publicly available datasets, which might not be diverse enough or representative of the true forensic variance.

Yusuf Artan et al. [14] (2024) Developed a fusion-based local matching technique that integrates handcrafted features with deep embeddings for latent print recognition. Increased complexity is brought about by the fusion process, contributing to more dependency on various stages of accurate feature extractions and, thus, more overhead for the system.

The study presented by Saket Pateriya et al. [15] (2024) propose the use of the scattering transform with the Shearlet Network (SSNet) to extract the fingerprint features with maximum robustness, and then a score-level fusion scheme is used

for higher authentication accuracy. May face difficulty adapting to highly distorted or occluded fingerprints in real-time environments.

Yuhang Qiu et al. [16] (2024) proposes IFViT, a two-stage framework for accurate and interpretable fingerprint matching. It performs dense fingerprint alignment using a Siamese ViT and then extracts fixed-length, interpretable representations via retrained ViTs with a fully connected layer. Experiments on public datasets demonstrate improved matching performance and interpretability. Depends on large training data and may involve heavy computational resources during deployment.

The general analysis of fingerprint verification and forgery detection with deep learning and machine learning techniques, by M. Genel, et al. [17] (2024), is facing new security threats such as fake fingerprint attacks. Given the SOCOing dataset, models were implemented under various configurations and hyperparameter settings for performance evaluation. Comparative results, showing the pros and cons of each method, enabled the selection of the best-performing models. Limited scope in real-time applications and relies on dataset-specific spoofing patterns.

For detecting spoofs in contactless fingerprint systems, which are increasingly being developed because of their convenient and hygienic benefits, Kanchana Rajaram et al. [18] (2024) propose CLNet, a deep learning approach. Existing methods for spoof detection often work with a limited set of features, resulting in low accuracy. Trained on the newly created S-CLAF dataset, CLNet achieved accuracy on the order of 99.07%, and it also provided high results on generalization: 98.32% on LivDet 2015 and 99.38% on the IIT Bombay dataset, bettering the results of the current state-of-the-art approaches. Performance may degrade when exposed to unseen spoofing techniques or poor lighting conditions.

H. M. Mishra and fellow analysts in 2024 [19] worked in Minutia-based mapping and Convolutional Neural Networks (CNNs), whereby deep learning means go into fingerprint matching to further its accuracy and speed. The uniqueness and permanence of fingerprints give these methods a great deal toward being implicated in modern biometric authentication and forensic investigations. Some conventional enhancement techniques may be ineffective on extremely noisy or partial prints.

A. Nóbrega et al. [20] (2024) provides an interesting possibility to produce more efficient minutiae descriptors for latent fingerprint identification, without needing private datasets. Experiments on NIST SD27 confirm an increase in hit rate of 6.59% over commercial tools, thus validating the strength of self-supervision and data augmentation methods for latent fingerprint recognition. Synthetic data may not fully capture real-world latent fingerprint distortions.

Abdulrasool Jadaan Abed – et al. [21] (2024) proposed a fingerprint identification approach using deep learning specifically geared toward low-quality fingerprint images. Experimental results demonstrate that this approach is more accurate and more robust under adverse conditions than conventional local minutia methods. This work stresses that there remains a need to innovate in biometric systems and suggests that fusion of multimodal biometrics may improve the performance further when coming to real applications. Performance may drop without pre-enhancement or on highly distorted fingerprints.

In 2024, X. Guan et al. [22] proposed the PDRNet (Phase-aggregated Dual-branch Registration Network) to allow for enhanced dense registration of fingerprints by aligning pairs down to the pixel level. Extensive experiments across different datasets show that PDRNet truly meets the state-of-the-art accuracy and robustness paradigm, while still maintaining competitive efficiency in fingerprint registration. Complex architecture may hinder real-time deployment or mobile implementation.

The list of applications discussed by A. Juneja, et al. [23] (2024) is ever-changing. Recent developments in fingerprint recognition reviewed include contactless identification using CNNs. Identification may also follow a hygienic minutiae-based process. Indoor positioning systems rank individuals against radio signals using ML models: k-NN and SVM series. Browser fingerprinting passively recognizes users by identifying unique browser configurations.

D. Mari et al. [24] (2024) carry out the first deeper investigation into the suitability of learning-based image codecs such as JPEG-AI for storing fingerprint images, where compression artifacts might affect the extraction of biometric features. They do provide a 47.8% BD rate reduction and a +3.97 dB PSNR gain without forfeiting automatic identification accuracy and human readability. May still need optimization for edge devices with limited decoding capacity.

B. GAN-Based Fingerprint Reconstruction and Selective Enhancement

Manjarini Mallik et al. [25] (2025) proposed VL-GAN to overcome data scarcity as well as labeling errors in fingerprinting-based indoor localization. They design a novel Label-to-Vector algorithm for converting the location labels into

probabilistic distance vectors. The architecture consists of a generator, a discriminator, and a label generator that acts as a classifier.

The Dual Residual Network (DRN), proposed by Misaj Sharafudeen et al. [26] (2025), detects artificially synthesized biomedical images, focusing upon CT nodules and dermatological lesions. It got near-perfect accuracy for detection (98.80% for nodules and 98.97% for lesions), with good sensitivity and specificity.

Dharmalingam Muthusamy et al. [27] (2025) announced a novel LKPR-PGAN method for enhancing latent fingerprint images for improved identification accuracy and speed. The system goes through five stages of processing: Laplace kernelized filtering, ROI segmentation, piecewise regression, and Progressive GAN. The experimental results show much better accuracy and less time needed than the existing techniques.

The authors Zhenzhou Jin et al. [28] (2025) propose the Conditional Generative Diffusion Model (CGDM) for the purpose of reconstructing fine-grained Channel Fingerprints from coarse-grained Channel Fingerprints in massive MIMO systems. Experimental results witnessed the improvements in reconstruction capability and scale of use across zero-shot generalization against methods that came before.

Seyed Rasoul Hosseini et al. [29] (2025) proposed WaFusion, a new framework that attempts to generate realistic morphed face images from wavelet decomposition and diffusion models for biometric analysis. The approach becomes the new standard for efficient and secure face morph generation.

S. Wu et al. [30] (2025) proposed a new indoor positioning framework combining a Location-Conditioned Variational Autoencoder (LCVAE) and a multi-task CNN, namely LCVAE-CNN. The LCVAE refines the RSSI fingerprints through dual-stream encoding, geospatial loss, and conditional augmentation to yield better quality data and spatial consistency. Comparative tests on benchmark datasets demonstrated higher accuracy than state-of-the-art methods with smaller errors.

The authors T. Xiang et al. [31] (2025) propose a semi-supervised learning approach for reconstructing RSS fingerprinting databases termed MoDeFA, which leverages only partially labeled data for retraining, thereby cutting down on the expensive site surveys. Extensive experiments on five datasets demonstrated that MoDeFA outperforms the state-of-the-art algorithms even when only 30% of the data have labels.

Weidi Huang et al. [32] (2025) proposes ADNet, an attribute disentanglement network for the protection of soft-biometric privacy under face recognition systems while protecting identity. A control factor enables the level of privacy to be adjusted for different scenarios. Experiments show that ADNet performs better than existing methods for controllable multi-attribute privacy protection.

In light of data scarcity and poor sample quality in indoor finger-printing, high-quality HDRF fingerprints are generated through conditional diffusion model (CDM) based framework proposed by Lyu et al. [33] (2025). A reduction of up to 16% in positioning error can be achieved when generated fingerprints are used.

Dongdeok Kim et al. [34] (2025) propose an approach named FALoc, a feature-level augmentation framework that enhances Wi-Fi fingerprinting-based indoor localization when faced with missing or unreliable RSSI data. Observations guide them in intelligently imputing or removing RSSIs, thus improving data quality. Experimental results on two datasets demonstrate that FALoc reduces localization error by up to 12.9%, outperforming MLP baselines.

Table 1: Deep Learning Approaches for Fingerprint Verification

Ref No. (Author, Year)	Technique Used	Key Features	Dataset Used	Results	Limitations
Abdul Wahab et al. [17] (2024)	GAN-based enhancement	Optimizes minutiae and ridge preservation	Not specified	Improved fingerprint clarity and identification	Scalability, stability, and standardization issues
Temirlan Meiramkhanov et al. [18] (2024)	CNN + Gabor filters	High robustness to altered prints, hybrid classifiers	Sokoto Coventry	Achieved 94% recognition accuracy	Scalability, stability, and standardization issues
Milind B Bhilavade et al. [19] (2024)	Minutiae & DL-based reconstruction	Two techniques for reconstructing poor-quality prints	Not specified	Minutiae: 82–99.99%; DL: 23–94% accuracy	DL-based performance varies; sensitive to quality

Hongtian Zhao et al. [20] (2024)	ResNet + GIoU-guided NMS	End-to-end minutiae extraction with outlier suppression	NIST SD4, FVC2004	Outperforms existing minutiae extraction models	Scalability, stability, and standardization issues
Sahar A. El_Rahman et al. [21] (2024)	CNN-based multimodal fusion	Fusion of fingerprint & ECG; sequential and parallel strategies	MIT-BIH, FVC2004	Sequential fusion achieved AUC of 0.99	Scalability, stability, and standardization issues
[41] Manjarini Mallik et al. (2025)	VL-GAN (Vectorized Labeled GAN)	Label-to-Vector conversion, SRFG strategy, Generator-Discriminator-Classifier setup	Not specified	Enhanced indoor localization data generation	Dataset details and cross-environment validation not explored
[42] Misaj Sharafudeen et al. (2025)	Dual Residual Network (DRN)	Low-frequency fingerprint analysis, Gradient-based interpretability	CT nodules, Dermatological lesions datasets	98.80% & 98.97% detection accuracy	Focused only on CT and skin images, generalization unclear
[43] Dharmalingam Muthusamy et al. (2025)	LKPR-PGAN	Laplace filtering, Piecewise regression, ROI segmentation, Progressive GAN	Not specified	High minutiae accuracy and speed	Dataset info and performance under noisy backgrounds not mentioned
[44] Zhenzhou Jin et al. (2025)	Conditional Generative Diffusion Model (CGDM)	ELBO optimization, one-shot pruning, knowledge distillation	Massive MIMO systems	High-quality reconstruction, scalability, zero-shot generalization	Specific dataset names and comparison metrics not detailed
[45] Seyed Rasoul Hosseini et al. (2025)	WaFusion (Wavelet + Diffusion Model)	Preserves structural details, Efficient morph generation	FERET, FRGC, FRLL, WVU Twin	State-of-the-art APCER, BPCER, EER metrics	Limited to face morphing; cross-modality application not discussed
[46] S. Wu et al. (2025)	LCVAE-CNN	Dual-stream encoder, Geospatial loss, Multi-task CNN	Indoor localization datasets	Improved floor classification & coordinate regression	Dependency on labeled data; scalability to large-scale areas untested
[47] T. Xiang et al. (2025)	MoDeFA (Semi-supervised learning)	Deep regression, Self-attention denoising	Five RSS datasets	Effective with only 30% labeled data	Performance with real-time data not explored
[48] Weidi Huang et al. (2025)	ADNet (Attribute Disentanglement)	ADM, Controllable privacy levels, Perturbed image generation	Face datasets with attributes	Better privacy protection with preserved identity	Focused on soft-biometric privacy only
[49] Z. Lyu et al. (2025)	Conditional Diffusion Model (CDM)	HDRF synthesis, Mahalanobis distance for sample selection	Indoor positioning system datasets	16% reduction in localization error	Assumes stable environment for HDRF generation
[50] Dongdeok Kim et al. (2025)	FALoc (Feature-level augmentation)	Bipartite graph, Variational Graph Autoencoder (VGAE)	Two indoor localization datasets	12.9% localization error reduction	May be sensitive to large missing data ratios

III. CHARACTERISTICS AND CHALLENGES OF LATENT FINGERPRINTS

Latent fingerprints are created when inadvertent friction ridge impressions are deposited on a surface by natural secretions from the hand. Unlike rolled or plain prints taken in a controlled environment, latent prints are usually partial, smudged,

or degraded by forces applying thereto, so to speak, during uncontrolled acquisition. Such prints, in particular, are either invisible or faint to see with the naked eyes and require some sort of enhancement in order to be analyzed. Their forensic value lies in them being the most common type of fingerprint to be found at crime scenes, thus being of utmost importance for biometric identification and criminal investigations. Still, the very nature of their formation and the quality of their capture makes the extraction of reliable features, mainly minutiae points that are key for matching and identification, a tremendous challenge.

Several distortions and noise factors affect the quality of latent fingerprints. Typical issues are smudging; overlap of prints; prints being deposited by varying, often inappropriate, stuffs of pressure; small incomplete ridge pattern; degradation of fingerprint by nature in the fingerprint powder environment like dust moisture, etc.; whereas these corrupt feature promote noise and artifacts to obstruct ridge flows, complicate the orientation field estimation, and hinder minutiae detection. Background clutter and surface curvature may likewise result in false features masking the timely marking of the ridge and leading to an equal bad enhancement result capable of increasing false match rates.

The complexity and variability of latent fingerprints make traditional acquisition and preprocessing methods inadequate. Histogram equalization, Gabor filtering, FFT-based enhancement all work well for high-quality, rolled prints but are less friendly when applied to noisy, partial, and distorted latent impressions. These methods are usually quite rigid, relying on predefined rules and handcrafted filters that are not adaptable enough to the variations found among print conditions. Furthermore, segmentation errors during preprocessing can lead to the loss of valuable regions or the inclusion of irrelevant background areas. Consequently, traditional pipelines are often unable to prepare latent prints well enough to yield accurate minutiae detection and subsequent identification and thus utilize more robust, learning-based approaches.

IV. Deep Learning for Latent Fingerprint Enhancement

The deep learning paradigm has thereby ushered in novel means for latent fingerprint enhancement, giving rise to data-driven approaches that are designed to meet the challenges of low-quality, partial, and noisy fingerprint impressions. Among the most popular architectures, Convolutional Neural Networks (CNNs) stand out, given their ability to learn hierarchical feature representations straight from raw fingerprint images. CNN-based approaches extract ridge patterns through convolutional operations, suppress undesired background noise, and enhance visibility of important details such as ridge endings and bifurcations. These models have shown greater effectiveness in learning local features and are generally used in joint frameworks for enhancement and minutiae extraction. Still, CNNs face limitations in grasping long-range dependencies; hence, their ability to model the global ridge structure in degraded latent prints may remain greatly restricted.

Thus, in order to regain some of these functionalities, GANs and autoencoders have been exploited in the restoration and enhancement of fingerprints. GANs contain two competing networks called the generator and discriminator, which produce very realistic fingerprint images. In latent fingerprint enhancement, GANs will be trained to generate clean ridge patterns that closely resemble those in a high-quality rolled print while discarding noise and distortions. Autoencoders work by learning how to compress and reconstruct fingerprint images, capturing the essential features in the encoding phase and restoring them during decoding. The variants, such as denoising autoencoders, have proven to be effective in aiding ridge structure enhancement from noisy inputs, thus suitable for latent fingerprint preprocessing.

Further hybrid deep architectures find mingling with various fine properties of a few models. CNNs allowed by Vision Transformers (ViTs) or attention mechanisms are thus well suited for the preservation of local details and global context modeling and enhancement with improved performance. Transfer learning is another take with some pre-trained models on large image sets fine-tuned for fingerprint-specific tasks. Such helps lessening the scarcity of annotated latent fingerprint data while speeding up convergence with no compromise on performance. Putting it all together, these deep learning methods factor in a shift from a handcrafted enhancement pipeline toward intelligent, scalable, and robust systems that can be used in real-world forensic and biometric applications.

V. Minutiae Detection Methods

Minutiae detection constitutes a vital step in fingerprint recognition systems that concentrate on individual ridge details like ridge endings and bifurcations from more enhanced images of fingerprints. After the latent fingerprint has first been preprocessed and enhanced (usually by the aid of deep learning models such as CNNs, GANs, or autoencoders), it is then time to apply minutiae algorithms for extracting those fine-grained features required for matching and identification. In this stage, basically, thinning reduces ridge structures to a thin one-pixel width, while then various topological patterns corresponding to minutiae points are detected. Certain conventional rule-based methods use well-defined heuristics and morphological operations in detecting minutiae from binarized and skeletonized images. These methods are, therefore, simple and interpretable. On the other hand, married to image quality, they are highly sensitive to distortions and noise, thereby greatly spawning spurious minutiae or even missing real ones, especially when dealing with latent prints where clarity is poor.

Contrary to traditional techniques, these learning-based approaches use deep neural networks to examine images directly for minutiae from either grayscale or enhanced images without explicit thinning or binarization. Being trained on annotated fingerprint datasets, these models learn strong representations of ridge flow and minutiae patterns even under difficult circumstances of partial, noisy, or smudged prints. The new advancements in the architecture such as ResNet, U-Net, and Vision Transformer have been recently considered beneficial in enforcing spatial dependencies and false detections suppressions. The learning-based methods may also support the end-to-end pipeline in which minutiae detection is combined with enhancement and segmentation, leading to a better accuracy and consistency of the larger system.

Minutiae detection techniques are assessed for effectiveness using performance measures like Precision (minutiae correctly identified versus all minutiae detected), Recall (minutiae correctly detected versus all real minutiae), and Equal Error Rate (EER), which balances false acceptance and false rejection rates; others might consider FAR (False Acceptance Rate) and FRR (False Rejection Rate) so that the reliability of the system can be determined. Values for precision and recall must be very high so that minutiae can be detected correctly and with minimum false positives or missed recognition; this is important for real-life applications in biometric verification matching or forensics.

VI. Applications in Forensics and Biometric Systems

The forensic world and biometric systems need latent fingerprint enhancement and minutiae detection for accurate suspect identification, identity verification, and the creation of criminal databases. These methods improve the operation of an Automated Fingerprint Identification System (AFIS) for secure authentication in numerous security-sensitive applications.

A. Integration with AFIS and Criminal Databases

Latent fingerprint enhancement forms the nucleus of an enhanced Automated Fingerprint Identification System that matches captured prints against largescale criminal or civil databases. High-quality minutiae extraction doubles up to help match algorithms work faster and its accuracy enhance when interfacing with improper or partial latent prints collected at crime scenes. Enhancement through the use of deep learning methods, by means of reducing false matches, leads to better interoperability with national and international databases like FBI's IAFIS or INTERPOL systems. It fortifies law enforcement agencies' abilities to link suspects to several crimes and cold cases and establish identities across jurisdictions, relying on standardized and certified biometric evidence.

B. Use in Mobile Biometric Authentication

With the mobile origin of biometrics, latent fingerprint enhancement techniques are being tailored to vehicular real-time biometric authentication in immersed environments. Mobile fingerprint sensors allowed a print noisy or partial disturbed by changing lights or motion blur or even dry skin, which makes enhancement and minutiae extraction algorithms a must to be robust. Recently, deep learning models with CNN and lightweight-GAN architectures have been optimized for mobile deployment to guarantee quick processing without compromising accuracy. This combination allows enhanced security of mobile payments and unlocking devices and hence promotes biometric access in remote and resource-constrained sites for verifying applications.

C. Real-World Deployments

There are latent fingerprint enhancement deployments in forensic labs and security agencies worldwide. In the USA, latent print enhancement tools, used in tandem with the NGI (Next Generation Identification) system, are considered to enhance matching efficiency to the suspect more accurately. Automated systems for latent fingerprint analysis have been used in crime investigations by law enforcement agencies in the UK and India, using enhanced detection of fingerprint minutiae to aid fast and accurate results. Mobile AFIS units are utilized in border control and remote identity verification. These installations speak to the practicality, scalability, and game-changing potential of deep-learning-based latent fingerprint analysis in forensic and biometric scenarios.

VII. CONCLUSION

Numerous challenges are presented during the analysis of latent fingerprints due to distortion, partial impressions, and environmental noise. Traditional methods and stand-alone deep learning models have thus been unable to provide consistent and accurate minutiae extraction under such conditions. This review informs us that hybrid architectures in which CNNs extract local details while ViTs operate on global contexts-are being further improved in classification performance with attention mechanisms. Such systems improve robustness and interpretability while also being adapted to different qualities of inputs and sensor modalities. In addition, taking care of dataset issues by means of augmentation also supports improving generalization of models. All of those improvements essentially constitute a great leap toward stable and scalable latent fingerprint recognition systems for forensic and biometric applications.

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