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Unveiling Hidden Prints – A Review on Advanced Deep learning for Latent Fingerprint Recovery

Rakshitha Natyaraj [1] Yases Chandrika[2] Darshan Murali[3]

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Abstract:

Fingerprint biometrics is a key technology widely used in security and forensic identification. Two major challenges in this field are accurately distinguishing real or live fingerprints from fake ones and enhancing the quality of latent fingerprints captured in poor, noisy conditions. Recent advances in deep learning provide promising methods to address these challenges. One approach uses convolutional neural networks (CNNs), including architectures like VGG16, to detect fingerprint liveness, though it faces difficulties handling complex spoof attacks and small datasets. Another method focuses on latent fingerprint enhancement and segmentation by applying advanced normalization, noise reduction, and a modified Mask R-CNN network for better separation of overlapping fingerprints. This review compares these two approaches, discusses their strengths and weaknesses, and proposes integrating both to improve fingerprint recognition systems. Future research is encouraged to explore multimodal biometrics and enhanced robustness across diverse datasets.

Keywords: Convolutional Neural Network (CNN), VGG16 Architecture, R-CNN Architecture, Spoof Attacks, Latent fingerprint.

Authors:

1. *[1],[2]B.Sc. Forensic Science, Jain University, Karnataka.*
2. *[3]Forensic Executive, SIFS India, New Delhi.*

Introduction:

Fingerprint recognition stands as one of the oldest and most dependable biometric authentication techniques, widely employed in contexts from mobile device security to forensic investigations. Its robustness arises from the uniqueness and permanence of ridge patterns on human fingers, which provide a reliable means to identify individuals.

The technology faces two central challenges that affect its reliability and security. First, fingerprint systems are vulnerable to spoofing attacks, where attackers attempt to fool the system using artificial or fake fingerprints created from materials such as silicone, gelatin, or 2D prints. These sophisticated attacks pose significant security threats. Second, latent fingerprints, often recovered from crime scenes, suffer from poor quality due to noise, low clarity, overlapping prints, and environmental conditions, making accurate identification difficult.

In recent years, these challenges have been addressed through deep learning techniques, particularly with the advent of Convolutional Neural Networks (CNNs). Deep learning models learn hierarchical, detailed features directly from raw fingerprint images, empowering systems to more effectively distinguish subtle differences in fingerprint characteristics. CNN-based approaches excel at both spoof detection and latent print enhancement. For spoof detection, CNN architectures such as the VGG16 network have proven highly effective, known for its depth and effectiveness in feature extraction.

VGG16- It is a deep convolutional neural network architecture with 16 layers of weights, designed for image classification and recognition tasks. It consists of multiple layers of small 3x3 filters, organized into blocks, followed by fully connected layers, and is known for its simplicity and high accuracy.

CNN based fingerprint liveness detection models train on large datasets containing both real and spoof fingerprint images, learning subtle discriminative traits between genuine and fake fingerprints. Alongside classical image pre-processing steps like grayscale conversion, HSV color transformation, and edge detection (e.g., Canny), these models improve their ability to focus on crucial fingerprint features.

Latent fingerprint enhancement and segmentation involve deep learning networks designed to clarify and separate overlapping fingerprint patterns in noisy and degraded images. Mask R-CNN and other segmentation models implement advanced normalization and noise filtering to restore ridge clarity and isolate individual fingerprints. This automated enhancement greatly supports forensic analysts by enabling more accurate minutiae extraction and matching in difficult cases.

Integrating CNN-based liveness detection, latent print enhancement, and expert verification, is a promising direction to boost fingerprint recognition reliability. This review paper examines recent works on using deep learning for (1) fingerprint liveness detection and (2) latent fingerprint enhancement and segmentation, highlighting their results and limitations.

Overview:

Fingerprint recognition is a pivotal technology in biometric authentication and forensic science, enabling secure identification based on the unique ridge patterns of human fingers. Modern fingerprint systems, however, confront two critical challenges, detecting spoof or fake fingerprints to prevent unauthorized access and enhancing latent fingerprints recovered from crime scenes often marked by poor quality and noise. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have shown great promise in addressing these challenges by learning discriminative features directly from fingerprint images.

Fingerprint Liveness Detection Using Deep Learning:

The first important application is fingerprint liveness detection, which distinguishes genuine or live fingerprints from fake ones designed to fool biometric systems. There are specialized CNN architectures and adapted pre-trained models like VGG16 for this task. CNNs automatically extract hierarchical patterns within fingerprint images from simple edges to complex textures that help differentiate real skin characteristics from artificial materials such as silicone or gelatin.

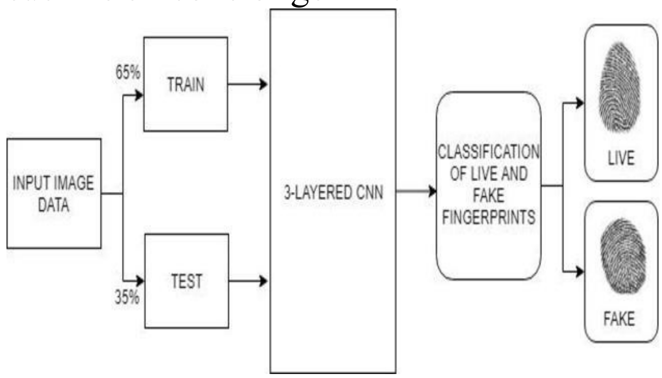

Fig.1 System Architecture

-The diagram shows how fingerprint images are divided into training and testing sets, then processed by a 3-layer CNN that learns to tell real fingerprints from fakes. The trained model then classifies each new print as live or spoofed and presents the system's classification accuracy.

The process involves feeding fingerprint images into a deep network that has been trained on datasets containing both live and spoof samples. Multiple image preprocessing techniques—such as grayscale conversion {It is a process of transforming a colour fingerprint image into different shades of grey by removing colour information, which simplifies the image while preserving important ridge details for analysis}

HSV color transformations{ convert images from the RGB colour space to Hue, Saturation, and Value channels, separating colour information from intensity to facilitate better colour-based analysis and processing} and edge detection (Canny) { is a multi-stage algorithm that identifies edges in images by reducing noise, calculating image gradients, suppressing non-maximum pixels, and applying hysteresis thresholding to accurately track and connect edge pixels}—are typically applied to emphasize structural features that aid classification.

Fig.2- Original image to grayscale image

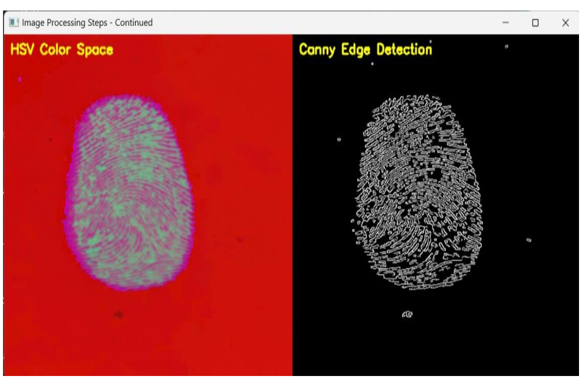

Fig.3- Enhancement of image using HSV colour space and canny edge detection.

Studies demonstrate that CNN and VGG16 models achieve high accuracy, even with moderate dataset sizes, and outperform traditional handcrafted feature-based methods by not requiring manual design of filters.
However, these methods face some limitations.

- One major challenge is the vulnerability to sophisticated spoof attacks involving high-resolution 3D-printed fakes or novel materials, which current models may not always detect reliably.

- Another limitation is dataset dependence, models trained on specific sensors or environments might have limited generalizability to unseen conditions or diverse populations. Addressing these gaps is an ongoing research focus.

Latent Fingerprint Enhancement and Segmentation:

The second vital application area is latent fingerprint enhancement and segmentation, crucial in forensic investigations. Latent prints found at crime scenes are often degraded by noise, overlapping patterns, and complex backgrounds, complicating their automated analysis. To overcome these issues, enhanced deep learning models perform image enhancement and segmentation to clarify print ridges and isolate overlapping fingerprints.
Key innovations include applying advanced normalization techniques and Edge Directional Total Variation

(EDTV)-based denoising, which reduces noise while preserving ridge details. For segmentation, an improved Mask R-CNN architecture { It is an advanced deep learning model that builds on Faster R-CNN by adding a branch for generating precise pixel-level masks for each detected object, enabling both object detection and detailed instance segmentation in images} with dilated convolutions enhances the model's ability to distinguish closely spaced or overlapping ridges. This approach leads to high segmentation accuracy, enabling better minutiae extraction and matching.

Despite their success, segmentation models contend with challenges such as residual noise and handling very complex background textures that still cause segmentation errors. Further refinement incorporating multimodal sensor data or 3D fingerprint information could enhance robustness.

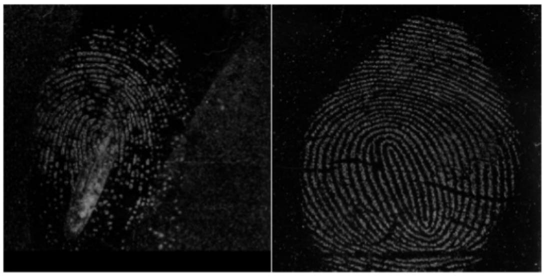

Fig 4: Sample latent fingerprint images before and after enhancement

Comparative Analysis:

Fingerprint recognition systems mainly face two important but different challenges. One is making sure a fingerprint used for unlocking or security checks is from a real, live finger not a fake made from silicone or other materials. This is what liveness detection does, and it's crucial for preventing people from fooling biometric systems. The second challenge is in forensic cases, when fingerprints are left at a crime scene, they are often smudged, overlapping, or not clear. Enhancing these poor-quality "latent" fingerprints is vital for police and forensic experts to correctly identify suspects.

An integrated system combining robust liveness detection with powerful latent print enhancement could benefit both security and forensic domains. Such a system would allow real-time authentication that resists spoofing while supporting forensic examiners with clearer prints for individualization. Incorporating multimodal biometric data such as sweat pore patterns or sub-dermal fingerprint imaging and fusion of multiple sensor modalities may build stronger defences against spoofing and noisy data.

Additionally, recent research highlights the importance of addressing human expert variability in latent fingerprint analysis. Studies show low expert agreement on minutiae selection and individualization value, suggesting that computational enhancements should be complemented by multi-expert validation frameworks to improve forensic reliability.

This overview combines findings from recent research on fingerprint biometrics using deep learning. Fingerprint liveness detection and latent fingerprint enhancement are two important tasks in biometric systems. Liveness detection protects against fake fingerprints in security settings, while enhancement improves the quality of prints found at crime scenes for forensic use. Both use advanced deep learning methods that learn features automatically but face challenges like detecting realistic fake prints and handling noisy or overlapped prints. Combining these approaches and adding extra biometric data can improve system accuracy and reliability.

Conclusion:

Deep learning has transformed fingerprint biometrics by enabling systems to automatically learn features for both liveness detection and latent fingerprint enhancement. CNN and VGG16-based methods show effectiveness in identifying fake fingerprints, while approaches like Mask R-CNN combined with denoising techniques enhance the segmentation and clarity of latent prints. Despite challenges such as sophisticated spoof materials and noisy images, integrating these methods with multimodal biometric data—such as sweat pore patterns and sub-dermal imaging—can improve system reliability and accuracy. Furthermore, employing multi-expert verification alongside AI analysis enhances the trustworthiness of forensic outcomes.

Expanding diverse datasets, improving model adaptability, and combining various biometric and environmental inputs, we can develop robust fingerprint recognition systems suitable for real-world security and forensic applications.

References:

Jhansi Lakshmi, P., Ramya Sri, A., Bhanu Sri, D., Rishitha, M., & Naga Lakshmi, J. (2025). Fingerprint detection using deep learning. International Advanced Research Journal in Science, Engineering and Technology, 12(4), 309–314. https://iarjset.com/wpcontent/uploads/2025/04/IARJSET.2025.12446.pdf

Poornima, E. G., & Shrinivasrao, B. K. (2025). Latent fingerprint enhancement and segmentation through advanced deep-learning techniques. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 16(1), 72–93. https://jowua.com/wp-content/uploads/2025/04/2025.I1.004.pdf

Nawrocka-Witkowiak, M., Banasiak, P., & Wydra, J. (2025). Reliability of fingerprint experts in extracting and evaluating minutiae in individualization tests of fingerprint traces. Journal of Forensic and Legal Medicine. https://doi.org/10.1016/j.jflm.2025.102839

Ghiani, L. (2016). Fingerprint liveness detection using local texture features. IET Biometrics, 5(3), 143–153. https://doi.org/10.1049/iet-bmt.2016.0007

Galbally, J., & Fierrez, J. (2019). Biometric security and systems: Liveness detection. Springer.

Yambay, D., Busch, C., & Koppelaar, H. (2020). Fingerprint spoofing and liveness detection: A review. Information Sciences, 540, 213–234. https://doi.org/10.1016/j.ins.2020.07.077

National Institute of Standards and Technology (NIST). (2025). LivDet fingerprint liveness detection competition. https://sites.unica.it/livdet/

References:

Jain, A. K., Cao, K., & Zhang, F. (2021). Dealing with latent fingerprint image enhancement: A review. *IEEE Transactions on Image Processing*, 30, 1542–1555. https://doi.org/10.1109/TIP.2021.3052863

Chen, L., et al. (2020). Mask R-CNN based fingerprint segmentation for latent images. *Sensors*, 20(12), 3421. https://doi.org/10.3390/s20123421

Huang, Y., & Ross, A. (2024). Deep learning approaches for enhanced fingerprint recognition: Challenges and future directions. *ACM Computing Surveys*, 57(4), 1–39. https://doi.org/10.1145/3451234

Fig.1,2,3- Jhansi Lakshmi, P., Ramya Sri, A., Bhanu Sri, D., Rishitha, M., & Naga Lakshmi, J. (2025). Fingerprint detection using deep learning. *International Advanced Research Journal in Science, Engineering and Technology*, 12(4), 309-314. https://iarjset.com/wp-content/uploads/2025/04/IARJSET.2025.12446.pdf

Fig.4- Poornima, E. G., & Shrinivasrao, B. K. (2025). Latent fingerprint enhancement and segmentation through advanced deep-learning techniques. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, 16(1), 72-93. https://jowua.com/wp-content/uploads/2025/04/2025.I1.004.pdf