**IAES International Journal of Artificial Intelligence (IJ-AI)**
Vol. 14, No. 6, December 2025, pp. 4739~4748
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i6.pp4739-4748


# Advancements in latent fingerprint recognition: a comprehensive review of techniques and applications

**Nandita Manchanda[1], Sanjay Singla[1], Gopal Rathinam[2]**
[1]Department of Computer Science and Engineering, Chandigarh University, Mohali, India
[2]Department of Information and Communication Engineering, University of Buraimi, Al Buraimi, Oman

**Article Info**

***Article history:***

Received Jan 21, 2025
Revised Sep 25, 2025
Accepted Oct 16, 2025

***Keywords:***

Enhancement
Latent fingerprint
Matching
Recognition
Reconstruction

**ABSTRACT**

The identification of individuals has been in greater demand, whether it's for criminal investigation, law enforcement, or the basic attendance marking system. Fingerprints are one of the most reliable and dependable methods for biometric identification systems; as such, they are crafted in the womb. Latent fingerprints refer to inadvertent impressions that are left behind at crime scenes and are of utmost importance in the field of forensic investigation and verification of the authenticity of an individual. However, because these impressions are unintentional, the quality of the prints uplifted is often poorer. To enhance the overall accuracy of fingerprint recognition, it is required to develop approaches that enhance the accuracy and reliability of existing techniques. Therefore, this paper provides a detailed analysis of the existing techniques for the reconstruction, enhancement, and matching of latent fingerprints.



***Corresponding Author:***

Nandita Manchanda
Department of Computer Science and Engineering, Chandigarh University
Mohali-140413, Punjab, India
Email: nandita.malik2721@gmail.com

## 1. INTRODUCTION

For more than a century, fingerprints have been considered the most reliable method of personal identification in the field of forensics. A person's fingerprints are frequently utilized as a means of determining their identity and understanding their uniqueness. So, human fingerprints have been utilized as vital evidence in criminal investigations [1]. Technological advancements have made it possible to enhance the effectiveness of scientific techniques for the acquisition and analysis of evidence. Also, the increase in the type and number of crimes committed by criminals has made it difficult for law enforcement agencies to prosecute them. Due to the growing digitization, imminent security risks such as hacking, phishing, and malware attacks have increased, so it has become essential to protect ourselves from these modern-day threats. Biometrics is a method used to safeguard oneself by relying on the inherent physical or behavioral characteristics of human beings for authentication reasons [2].

In today's digital age, unique physical traits such as fingerprints, palm prints, facial recognition, and iris patterns are extensively utilized for the identification of criminals. Because of their uniqueness, fingerprints are still regarded as highly significant and are the most widely used quality among all. As a result, fingerprint identification is widely utilized in various domains such as banking, finding missing children, and passport control. A latent fingerprint refers to an invisible or hidden imprint formed by the ridges of a finger on a surface, like glass or a doorknob. Several methods, such as dusting with fingerprint powder or employing chemical developers, can render these hidden impressions visible [3]. So, further processing of these fingerprints is required for the proper identification of criminals. The investigation team faces many challenges, like complex background noise, partial impressions, enhancement of poor-quality images, upliftment of fingerprints, and capturing of impressions from the crime scene [4]. These challenges provide researchers with insight into how to enhance and improve the performance of the identification systems. The latent fingerprint image processing involves a sequence of steps, as shown in Figure 1. The initial step is known as image acquisition, in which an image is uplifted from the background using different methods. In the second phase, the quality of the image captured in the initial phase is enhanced by improving the clarity of the ridge structure, reducing the noise, and adjusting the ridge/valley contrast. The third step is used for the restoration of the image, where the exact features of the degraded image that have been deteriorated due to blur, noise, dirt, scratches, and other factors are recovered. In the last phase, different algorithms are used to match the recovered image with the images available in the database [5].


Figure 1. Work flow of processing of latent fingerprints

There are some unique features of fingerprints that are used for the matching of latent fingerprints. These features are classified into three different levels known as level 1, level 2 and level 3 features.

i) Level 1 features

It includes basic patterns of fingerprints like the ulnar loop, radial loop, plain arch, tented arch, plain whorl, central pocket, and double loop. These features can be easily recognized and do not require any tools or methods for identification. Some of level 1 features are shown in Figure 2.

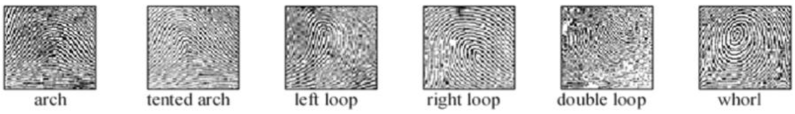


Figure 2. Level 1 features

ii) Level 2 features

Next are level 2 features that are more complex in nature as compared to level 1 features. It includes different components of minutiae like ridge ending, bifurcation, delta, spur, and ridge dot. Figure 3 shows the types of level 2 features. The fingerprints left at the crime scene are not clear due to noise, strains, and other factors; therefore, suitable enhancement and reconstruction techniques are required to get a good-quality image by eliminating spurious features.


Figure 3. Level 2 features

iii) Level 3 features

It is also known as permanent features such as scars, creases, line shapes, and warts. They are the most distinguishing features that help to improve performance efficiently and Figure 4 shows the different types of level 3 features. Hence, a combination of the above-mentioned features is used for accurate matching.

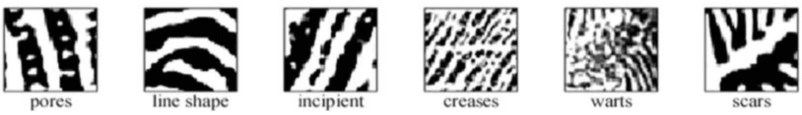


Figure 4. Level 3 features

## 2. RELATED WORK

This section highlights the existing techniques for upliftment, enhancement, reconstruction, and matching. It also includes a comparative analysis and applications of the existing techniques for different phases of latent fingerprint processing. Different phases of latent fingerprint processing are discussed as follows.

### 2.1. Upliftment techniques for latent fingerprints

Upliftment of latent fingerprints needs to be performed before the processing of latent fingerprints. There are different techniques for uplifting that are done by forensic experts. The selection of techniques depends upon the texture and porosity of the surface because every surface has its own unique properties [6]. Selecting a particular type of upliftment technique is very crucial, as this uplifted latent print forms the base of the enhancement, matching, and reconstruction step ahead. Good-quality uplifted latent prints would yield better final results. It is directly related to the fact that in order to extract maximum minutiae from an image, the investigation team must have good-quality uplifted latent prints so that matching performance doesn't get affected. In a nutshell, evidence should be handled carefully, and the upliftment of prints should also be done very precisely and carefully.

### 2.2. Enhancement techniques for latent fingerprints

The images obtained from the crime scene are of low quality due to noise, blood stains, and other factors. Enhancement of the uplifted image is necessary to get accurate features for proper identification. The different techniques available for enhancement are mentioned in Table 1. A novel approach named FingerGAN was designed that specifically improves the process of latent fingerprint enhancement. It is a constrained generation method that makes use of the generative adversarial network (GAN) for generating high-quality synthetic fingerprints [7]. In 2023, a preliminary approach was introduced for the enhancement of latent fingerprints by combining the capabilities of the U-net encoder and the ResNet-101 network [8]. A GAN based training model was proposed by Joshi *et al*. [9], that enhances the quality and accuracy of latent fingerprints. This method uses a mix of convolutional neural networks (CNN) and GAN to generate high-quality fingerprints. In 2022, Jindal and Singla emphasized the use of ant colony optimization (ACO) for latent fingerprint enhancement and matching purposes and based on the foraging behavior of ants to find solutions [10]. Next, the authors suggested the use of pores as a level 3 feature to improve the precision and efficiency of the fingerprint recognition process [11]. Further, a two-stage spectrum boosting technique with sparse autoencoder and matched filtering methods was introduced, and the input image was enhanced using various steps [12].

Table 1. Available enhancement techniques

| Authors | Year | Technique used | Dataset used | Performance evaluation metric | Remarks |
|---|---|---|---|---|---|
| Zhu *et al*. [7] | 2023 | FingerGAN | NIST SD14<br>NIST SD27<br>IIITD-MOLF | Minutia recovery accuracy<br>CMC curve | Achieves better identification performance with the optimization of minutiae information. |
| Wyzykowski and Jain [8] | 2023 | GPU-optimized Mixed architecture | NIST SD27 | Visual comparison | Enhancement Gabor layer is designed for estimating GPU computations. |
| Agarwal and Bansal [11] | 2021 | Pore extraction | IIITD latent Fingerprint | CMC curve | Pores provide additional information that helps in getting accurate results. |
| Jindal and Singla [10] | 2021 | ACO | NIST SD27 | Precision, recall, and F-score | An assignment graph is designed and used for final matching. |
| Huang *et al*. [13] | 2020 | PGAN | NIST SD27<br>NIST SD14 | CMC curve | Orientation estimation task improves the recognition accuracy. |
| Horapong *et al*. [12] | 2020 | Two-stage spectrum boosting | NIST SD4<br>IIITD-MOLF | CMC curve | A sparse autoencoder and matched filter boost the ridge spectra. |
| Joshi *et al*. [9] | 2019 | GAN approach | IIITD-MSLF<br>IIITD-MOLF | SSIM; CMC curve; Rank-50 | Improvement in the identification of foreground and background is required. |
| Qian *et al*. [14] | 2019 | DenseUNet | NIST SD27 | CMC curve | To achieve minimum requirement of image quality, an iterative enhancement with model is used. |
| Liu *et al*. [15] | 2019 | COOGAN | NIST SD27<br>NIST SD14 | NFIQ 2.0 score | To remove the low-quality area of an image, an estimation model is used. |
| Manickam and Devarasan [16] | 2019 | T2IFS | FVC 2004<br>IIITD latent fingerprint | Minutiae match score | Enhancement of ridge flow and structure is necessary before feature extraction. |
| Krish *et al*. [17] | 2019 | EMD | NIST SD27 | CMC curve<br>Rank-1 | Three minutia-based matchers are used to improve rank. |
| Rani and Vasanth [18] | 2019 | Multi-scale patch-based sparse representation | NIST SD27 | Epoch 10 | Texture components act as useful information in eliminating the non-fingerprint patterns. |
| Chaidee *et al*. [19] | 2018 | Spectral dictionary | NIST SD14<br>NIST SD27 | CMC curve | Preserves and improves the details of ridge structure and highly curved ridges. |
| Liban and Hilles [20] | 2018 | DTV model | NIST SD27 | RMSE<br>PSNR | With enhancement, the matching accuracy is improved by 30%. |

A progressive generative adversarial network (PGAN) used by authors for the enhancement of latent fingerprints by creating high-quality images from low-quality images by the use of two different neural networks [13]. In 2019, a DenseUNet-based technique was developed for the enhancement of latent fingerprints [14]. The high-quality images were overlapped with patterns and structured noise to generate training data. A novel approach named cooperative orientation generative adversarial network (COOGAN) was presented for image-to-image translation and also incorporates orientation constraints into it for more accurate results [15]. The authors recommended the use of a type-2 intuitionistic fuzzy set (T2IFS) for the enhancement of the features that are being extracted for latent fingerprint recognition [16].

The use of extended minutia types was suggested by Krish *et al.* [17] for improving automated latent fingerprint identification and introduced a new technique called extended minutia descriptor (EMD). In 2019, multi-scale patch-based sparse representation and neural network-based matching using Gabor functions were used to improve the latent fingerprint images [18]. With this approach, the fingerprint image was decomposed into different frequency bands, and Gabor filters were utilized to improve the valley and ridge structures of the fingerprints. Next, an approach was introduced by the authors that makes use of the spectral dictionary method for the pre-enhancement of latent fingerprints, and the spectral dictionary of known fingerprint patterns was first constructed and then later used to filter the latent fingerprint image [19]. Lastly, a method was developed by Liban and Hilles [20] in the year 2018. This method reconstructs the lost minutiae by using the directional total variation (DTV) model. The DTV model was a modified version of the total variation (TV) model, which factors in the directional characteristics of the image [20].

### 2.3. Reconstruction techniques for latent fingerprints

Reconstruction of latent fingerprints is a crucial step in the processing of latent fingerprints, as the fingerprints uplifted from the crime scene are blurred, incomplete, and may contain stains or noise. Table 2 shows the various available techniques for the reconstruction of the latent fingerprint image. In 2023, a novel framework was proposed that utilizes the GAN for latent fingerprint synthesis and reconstruction [21]. A deep learning algorithm using U-net architecture was presented in 2022 and evaluates the performance using mean absolute error (MAE) and mean square error (MSE) [22]. Next, a complete representation GAN (CR-GAN) based restoration model was introduced that removes the noise from the input image and produces a binarized fingerprint image as output [23]. In 2021, a CNN based approach was implemented for reconstructing the fingerprint images by extracting the minutiae features from the obtained image and replicating the input for obtaining the output while reducing the number of reconstruction errors [24].

Table 2. Available reconstruction techniques

| Authors | Year | Technique used | Dataset used | Performance evaluation metric | Remarks |
|---|---|---|---|---|---|
| Bouzaglo and Keller [21] | 2023 | GAN | NIST SD4<br>NIST SD14 | Identification<br>Accuracy<br>FAR | Synthetic fingerprints generated are more realistic and can deceive verification of fingerprints. |
| Pan *et al*. [22] | 2022 | U-net architecture | NA | MSE<br>MAE | It reduces the MSE and MAE considerably. |
| Joshi *et al*. [23] | 2022 | CR-GAN | IIITD-MOLF<br>rural Indian fingerprint | NFIQ SSIM<br>Rank-50 | Channel refinement can be applied to the other phases of automated fingerprint recognition system. |
| Saponara *et al*. [24] | 2021 | CNN | FVC 2004 | MSE | Data augmentation approaches can be used to reduce MSE. |
| Xu *et al*. [25] | 2020 | AugNet framework | NIST SD27<br>IIITD latent fingerprint | Rank-K identification accuracy | It significantly improves the identification performance and visual evaluation. |
| Lee *et al*. [26] | 2020 | Pix2Pix model | NIST SD4 | FID value<br>FMR | Proposed method has better false recovery rate as compared to other conventional methods. |
| Gupta *et al.* [27] | 2020 | OPR method | FVC 2002<br>FVC 2004 | Goodness index<br>Type1 attack TAR | With the utilization of dictionaries, the reconstructed image looks more realistic. |
| Wong and Lai [28] | 2020 | OFFIENet | FVC 2002<br>FVC 2004 | PSNR<br>TMR/FMR | Consideration of orientation feature of the fingerprint gives better results. |
| Dabouei *et al.* [29] | 2018 | cGAN | IIITD latent fingerprint<br>IIITD-MOLF | Rank-25<br>Rank-50 | It considerably improves the matching accuracy for latent fingerprints. |

Further, an AugNet framework was proposed for latent fingerprint synthesis to transform a clean fingerprint image into a latent fingerprint image [25]. A machine learning-based model named Pix2Pix was presented for generating fingerprint images that look more natural by utilizing skeleton fingerprint image features [26]. In 2020, a novel approach was presented for the enhancement and reconstruction of fingerprints. In this method, a fingerprint image was decomposed into two components known as phase and orientation components [27]. Next, a CNN-based model named orientation field-corrected fingerprint image enhancement network (OFFIENet) was introduced in the year 2020 [28]. It utilizes the ridge orientation information for recovering the ridge structures of the fingerprint. Further, a method based on the conditional generative adversarial network (CGAN) was presented for the reconstruction of fingerprints that helps to generate four additional maps known as an orientation map, a frequency map, a ridge map, and a segmentation map for each latent fingerprint input image [29].

### 2.4. Matching techniques for latent fingerprints

After reconstruction of the fingerprint image, matching with the original fingerprint is done. Matching is considered the last phase of the processing of latent fingerprints. The techniques developed for matching of latent fingerprints are shown in Table 3. A hybrid framework was introduced in the year 2022 that helps in the identification of pores and minutiae points in the latent fingerprints to obtain more accurate results [30]. Further, an EDTV model-based Chan-Vese active contour technique was proposed for the segmentation and matching of latent fingerprints [31]. Image segmentation was considered important as it removes background noise, stains, or any unwanted part from the foreground.

Table 3. Available matching techniques

| Authors | Year | Technique used | Dataset used | Performance evaluation metric | Remarks |
|---|---|---|---|---|---|
| Singla *et al*. [30] | 2022 | Fully convolution neural network (FCN) | CSRC latent fingerprint touch-less database | Rank-k identification | Score level fusion enhances the accuracy of identification. |
| Jindal and Singla [10] | 2021 | ACO | NIST SD27 | Precision, recall, F-score, imilarity score | For accurate match results, ground truth values are used as benchmarks. |
| Hilles *et al*. [31] | 2021 | Chan-Vese active contour segmentation | NIST SD27 | ROC<br>CMC<br>Rank-1 identification | For good images, matching accuracy is 72% AUC that is better than the conventional methods. |
| Gu *et al*. [32] | 2021 | Dense sampling | NIST SD27<br>IIITD-MOLF | CMC<br>Rank-1 identification | Precise registration method gives more accurate results as compared to coarse registration. |
| Deshpande *et al*. [33] | 2020 | CNNAI | FVC 2004<br>NIST SD27 | Confusion matrix | Proposed model is robust against scale and rotation. |
| Nguyen and Jain [34] | 2019 | Pore extraction and matching | NIST SD30<br>NIST SD4 | CMC curve<br>Precision<br>Recall, F1-score | Pore matcher can improve the identification with average number of minutiae. |
| Manickam *et al*. [35] | 2018 | SIFT | FVC 2004 IIITD latent fingerprint | Minutiae match score | Value of 1 is required in order to maintain the quality of the image. |
| Ezeobiejesi and Bhanu [36] | 2018 | Patch-based | NIST SD27<br>NIST SD4 | Rank-1 identification | With patch-based matching, identification accuracy has been significantly improved. |

A patch alignment and matching method proposed by Gu *et al*. [32] uses sampled points as key points instead of the minutiae extraction phase for matching latent fingerprints. It computes alignment parameters between different image patches and determines the similarities between them. In the year 2020, a model named combination of nearest neighbor arrangement indexing (CNNAI) based on a minutia-based CNN was introduced [33]. In this method, n local nearest neighbors of central minutiae were identified for matching, and rotation-scale invariant feature vectors were generated. Next, Nguyen and Jain [34] introduced a framework that performs end-to-end pore extraction and matching. It uses level-3 pore features for latent fingerprint matching and comprises two modules named minutiae and pore matching. If the decision based on minutiae was ambiguous, then pore matching was used as a complementary step for the matching purpose.

Further, a scale-invariant feature transform (SIFT) feature point matching technique was presented that utilizes the associated descriptors for comparing each local extrema and also employs an intuitionistic type-2 fuzzy set for the contrast enhancement [35]. In 2018, a patch-based matching technique was presented, and two neural networks, named the representation learning network (RLN) and similarity learning network (SLN), were used in this method [36].

## 3. DATABASES AVAILABLE FOR LATENT FINGERPRINTS

Latent fingerprint databases, rolled and plain databases are three categories into which fingerprint databases can be mainly classified. Plain fingerprints are used commercially, while rolled and latent fingerprints are used for forensic-related purposes. Simple photography and various chemicals are used for capturing latent fingerprints, to get plain fingerprints, simple impressions of fingers using machines fitted with sensors are used [37]. By rolling the fingers from either side, one can get the rolled fingerprints [38]. Some of the commonly used databases are as follows.

### 3.1. IIITD latent fingerprint database

It is named the Indraprastha Institute of Information Technology Delhi (IIITD) latent fingerprint database. It contains impressions of all 10 fingers with 15 subjects, and a total of 1,046 fingerprint impressions are there [39]. These samples have been collected from two different backgrounds, i.e., tiles and cards. Mated 500 ppi and 1,000 ppi fingerprint sensor impressions are also available [40]. The 500 ppi images are captured with the help of Crossmatch L1scan, while 1,000 ppi images are captured using SecuGen Hamster IV.

### 3.2. IIITD-multi-sensor optical latent fingerprint database

It is known as the IIITD multi-sensor optical latent fingerprint (MOLF) database. It consists of 19,200 fingerprints that are collected from 100 subjects, and different methods such as CrossMatch, L-Scan Patrol, and Secugen Hamster-IV are used for the collection of the fingerprint samples. It is divided into six subsets named as DB1, DB2, DB3, DB3_A, DB4, and DB5 containing images of different sizes [41], [42].

### 3.3. IIITD-multi-surface latent fingerprint database

Multi-surface latent fingerprint (MSLF) database. It has a collection of 551 latent fingerprints from 51 subjects. Eight different surfaces, like transparent glass, compact discs, ceramic mugs, ceramic plates, steel glass, CD mailers, hardbound book covers, and paperback book covers, are used for the image capturing [43].

### 3.4. National Institute of Standards and Technology special database 27

It is called the National Institute of Standards and Technology special database 27 (NIST SD27). It is a publicly available database provided by NIST in collaboration with the Federal Bureau of Investigation (FBI). It has a collection of 258 fingerprint impressions left at the crime scene. It includes both 500 ppi and 1,000 ppi fingerprint samples [44], [45]. Each sample contains one latent fingerprint image, four sets of minutiae, and their matching ten print images that have been verified by the team of highly skilled latent examiners [46].

### 3.5. Fingerprint verification competition 2002

It is known that the fingerprint verification competition (FVC) evaluated in 2002. It comprises four databases DB1, DB2, DB3, and DB4, and each database contains 880 fingerprints in total [47]. Samples in DB1 and DB2 are collected using optical sensors named TouchViewII and FX2000 [48]. Using capacitive sensor 100 SC, images are captured and stored in DB3, whereas a fingerprint synthetic generation technique is used to collect images for DB4.

### 3.6. Fingerprint verification competition 2004

It is the third international FVC evaluated in 2004. It is categorized into four databases and each database contains 1,440 fingerprint impressions [49]. The two databases are collected through the optical sensors CrossMatch V300 and Digital Persona U.are.U 4000. The third and fourth database is collected using thermal sweeping sensor named the Atmel FingerChip, and the fourth database is collected through the synthetic generator technique SFinGe [50].

## 4. PERFORMANCE ANALYSIS

In this section, the performance of various techniques for different phases is discussed, which shows there is still a scope for improvement at different stages of automated fingerprint recognition. Different techniques use various performance metrics to evaluate and analyze the performance. Table 4 highlights the performance analysis of various techniques discussed in the previous sections.

Table 4. Performance analysis of latent fingerprint recognition techniques

| Phase | Author's name | Year | Technique | Results |
|---|---|---|---|---|
| Enhancement | Zhu *et al*. [7] | 2023 | FingerGAN | Rank-1 accuracy achieved is 76.36%. |
| | Jindal and Singla [10] | 2021 | ACO | Precision is 78.38%, 69.72%, and 63.39% for good, bad and ugly images. Recall is 98.86%, 89.41%, and 85.53% for good, bad and ugly images. |
| | Agarwal and Bansal [11] | 2021 | Pore extraction | Recognition rate at rank-1 achieved is 54%. |
| | Joshi *et al*. [9] | 2019 | GAN approach | Rank-50 accuracy is 35.6(IIITD-MOLF)<br>Rank-50 accuracy is 30.16(IIITD-MSLFD) |
| | Krish *et al*. [17] | 2019 | EMD | Rank-1 accuracy is 71.4 with individual matcher and approx. 82% with multiple matchers. |
| | Rani and Vasanth [18] | 2019 | Multi-scale patch-based sparse representation | At epoch 10, best training performance obtained is 7.8717e. |
| Reconstruction | Bouzaglo and Keller [21] | 2023 | GAN | Identification accuracy for Type-I and Type-II attack is 99.89% and 98.93% |
| | Pan *et al*. [22] | 2022 | U-net architecture | MSE ranges from 0.000 to 0.0007<br>MAE ranges from 0.0089, 0.0092 to 0.0095 |
| | Saponara *et al*. [24] | 2021 | CNN | Identification rates of 98.1%, 97%, 95.9%, and 95.02% are achieved on DB1, DB2, DB3, and DB4. |
| | Lee *et al*. [26] | 2020 | Pix2Pix model | FID value ranged from 105 to 171 that indicates excellent quality. |
| | Xu *et al*. [25] | 2020 | AugNet framework | Rank-10 Accuracy for NIST SD27, IIITD and IIITD-MOLF is 75.58%, 92.91%, and 43.29% |
| | Wong and Lai [28] | 2020 | OFFIENet | Rank-50 accuracy is 89.89% and 84.10% for good quality and low-quality latent fingerprints. |
| | Gupta *et al*. [27] | 2020 | OPR method | Type I attack: TAR is 97.95% on FVC2002 and 94.09% on FVC2004. |
| Matching | Singla *et al*. [30] | 2022 | FCN | Maximum identification rank-5 accuracy of 81.36% is achieved. |
| | Hilles *et al*. [31] | 2021 | Chan-Vese active contour | Rank-20 identification is 79% and 64% for good and ugly images. |
| | Jindal and Singla. [10] | 2021 | ACO | Similarity scores for good, bad and ugly images are 94.96%, 87.895, and 84.64%. |
| | Gu *et al*. [32] | 2021 | Dense sampling | Achieved rank-1 identification of 70.1%. |
| | Deshpande *et al*. [33] | 2020 | CNNAI | Rank-1 identification rate of 84.5% and 80% for NIST SD27 and FVC2004 respectively. |
| | Nguyen and Jain [34] | 2019 | Pore extraction | Rank-1 identification rate achieved is 98.1%.<br>Rank-5 identification rate achieved is 99.1% |
| | Ezeobiejesi and Bhanu [36] | 2018 | Patch-based | Rank-1 identification rate achieved is 81.35% |

## 5. CONCLUSION AND FUTURE DIRECTIONS

This paper provides a comprehensive overview of different techniques developed for different phases of automated fingerprint processing. In order to achieve high performance and more accurate results of an automated fingerprint recognition system, significant improvements are required at different phases of processing. During enhancement and reconstruction of latent fingerprints, various image processing techniques have been utilized to improve the quality of images and hence improve the efficiency of the matching process. Furthermore, the performance of the various techniques has also been analyzed that provides researchers an insight into how to improve the performance of latent fingerprint recognition. As latent fingerprints are considered crucial evidence in the identification of criminals, future work involves the development of novel techniques that generate accurate results in less time. Research in this area will help the law enforcement agencies for better identification of criminals and matching process or in biometric identification for different security systems.

## FUNDING INFORMATION

Authors state there is no funding involved.

## AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Nandita Manchanda | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | |
| Sanjay Singla | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Gopal Rathinam | ✓ | ✓ | | ✓ | | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

## REFERENCES

[1] R. N. Pramukha, P. Akhila, and S. G. Koolagudi, "End-to-end latent fingerprint enhancement using multi-scale generative adversarial network," *Pattern Recognition Letters*, vol. 184, pp. 169–175, Aug. 2024, doi: 10.1016/j.patrec.2024.06.022.

[2] A. K. Jain, J. Feng, and K. Nandakumar, "Fingerprint matching," *Computer*, vol. 43, no. 2, pp. 36–44, Feb. 2010, doi: 10.1109/MC.2010.38.

[3] B. Abebe, H. C. A. Murthy, E. A. Zereffa, and Y. Dessie, "Latent fingerprint enhancement techniques: a review," *Journal of Chemical Reviews*, vol. 2, no. 1, pp. 40–56, Jan. 2020, doi: 10.33945/SAMI/JCR.2020.1.3.

[4] T. Kumar and R. S. Garg, "The recognition of latent fingerprints using swarm intelligence based hybrid approach," *International Journal on Emerging Technologies*, vol. 11, no. 5, pp. 90–97, 2020.

[5] D. Ezhilmaran and M. Adhiyaman, "A review study on latent fingerprint recognition techniques," *Journal of Information and Optimization Sciences*, vol. 38, no. 3–4, pp. 501–516, May 2017, doi: 10.1080/02522667.2016.1224468.

[6] Priyanka and Shabeena, "A review on recovery of latent fingerprints on different substrates immersed under muddy water," *IP International Journal of Forensic Medicine and Toxicological Sciences*, vol. 7, no. 1, pp. 4–7, Apr. 2022, doi: 10.18231/j.ijfmts.2022.002.

[7] Y. Zhu, X. Yin, and J. Hu, "FingerGAN: a constrained fingerprint generation scheme for latent fingerprint enhancement," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 7, pp. 1–14, 2023, doi: 10.1109/TPAMI.2023.3236876.

[8] A. B. V. Wyzykowski and A. K. Jain, "Accelerated fingerprint enhancement: a GPU-optimized mixed architecture approach," *arXiv:2306.00272*, Jun. 2023.

[9] I. Joshi, A. Anand, M. Vatsa, R. Singh, S. D. Roy, and P. Kalra, "Latent fingerprint enhancement using generative adversarial networks," in *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*, IEEE, Jan. 2019, pp. 895–903. doi: 10.1109/WACV.2019.00100.

[10] R. Jindal and S. Singla, "Ant colony optimisation for latent fingerprint matching," *International Journal of Advanced Intelligence Paradigms*, vol. 19, no. 2, 2021, doi: 10.1504/IJAIP.2021.115247.

[11] D. Agarwal and A. Bansal, "A utility of pores as level 3 features in latent fingerprint identification," *Multimedia Tools and Applications*, vol. 80, no. 15, pp. 23605–23624, Jun. 2021, doi: 10.1007/s11042-020-10207-x.

[12] K. Horapong, K. Srisutheenon, and V. Areekul, "Progressive latent fingerprint enhancement using two-stage spectrum boosting with matched filter and sparse autoencoder," in *2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, IEEE, Jun. 2020, pp. 531–534, doi: 10.1109/ECTI-CON49241.2020.9158210.

[13] X. Huang, P. Qian, and M. Liu, "Latent fingerprint image enhancement based on progressive generative adversarial network," in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, IEEE, Jun. 2020, pp. 3481–3489, doi: 10.1109/CVPRW50498.2020.00408.
[14] P. Qian, A. Li, and M. Liu, "Latent Fingerprint enhancement based on DenseUNet," in *2019 International Conference on Biometrics*, IEEE, Jun. 2019, pp. 1–6, doi: 10.1109/ICB45273.2019.8987279.
[15] Y. Liu, Y. Tang, R. Li, and J. Feng, "Cooperative orientation generative adversarial network for latent fingerprint enhancement," in *2019 International Conference on Biometrics*, IEEE, Jun. 2019, pp. 1–8, doi: 10.1109/ICB45273.2019.8987356.
[16] A. Manickam and E. Devarasan, "Level 2 feature extraction for latent fingerprint enhancement and matching using type-2 intuitionistic fuzzy set," *International Journal of Bioinformatics Research and Applications*, vol. 15, no. 1, pp. 33-50, 2019, doi: 10.1504/IJBRA.2019.097994.
[17] R. P. Krish, J. Fierrez, D. Ramos, F. A.-Fernandez, and J. Bigun, "Improving automated latent fingerprint identification using extended minutia types," *Information Fusion*, vol. 50, pp. 9–19, Oct. 2019, doi: 10.1016/j.inffus.2018.10.001.
[18] R. J. Rani and K. Vasanth, "Latent fingerprint image enhancement using Gabor Functions via multi-scale patch based sparse representation and matching based on neural networks," in *2019 International Conference on Communication and Signal Processing*, IEEE, Apr. 2019, pp. 0365–0369, doi: 10.1109/ICCSP.2019.8697916.
[19] W. Chaidee, K. Horapong, and V. Areekul, "Filter design based on spectral dictionary for latent fingerprint pre-enhancement," in *2018 International Conference on Biometrics*, IEEE, Feb. 2018, pp. 23–30, doi: 10.1109/ICB2018.2018.00015.
[20] A. Liban and S. M. S. Hilles, "Latent fingerprint enhancement based on directional total variation model with lost minutiae reconstruction," in *2018 International Conference on Smart Computing and Electronic Enterprise*, IEEE, Jul. 2018, pp. 1–5. doi: 10.1109/ICSCEE.2018.8538417.
[21] R. Bouzaglo and Y. Keller, "Synthesis and reconstruction of fingerprints using generative adversarial networks," *arXiv:2201.06164*, Mar. 2023, [Online]. Available: http://arxiv.org/abs/2201.06164
[22] M.-S. Pan, C.-H. Fan, Y.-L. Lin, and H.-C. Hsu, "Optimization fingerprint reconstruction using deep learning algorithm," in *2022 17th International Microsystems, Packaging, Assembly and Circuits Technology Conference*, IEEE, Oct. 2022, pp. 1–3. doi: 10.1109/IMPACT56280.2022.9966693.
[23] I. Joshi, A. Utkarsh, P. Singh, A. Dantcheva, S. D. Roy, and P. K. Kalra, "On restoration of degraded fingerprints," *Multimedia Tools and Applications*, vol. 81, no. 24, pp. 35349–35377, Oct. 2022, doi: 10.1007/s11042-021-11863-3.
[24] S. Saponara, A. Elhanashi, and Q. Zheng, "Recreating fingerprint images by convolutional neural network autoencoder architecture," *IEEE Access*, vol. 9, pp. 147888–147899, 2021, doi: 10.1109/ACCESS.2021.3124746.
[25] Y. Xu, Y. Wang, J. Liang, and Y. Jiang, "Augmentation data synthesis via gans: boosting latent fingerprint reconstruction," in *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing*, IEEE, May 2020, pp. 2932–2936, doi: 10.1109/ICASSP40776.2020.9053801.
[26] S. Lee, S.-W. Jang, D. Kim, H. Hahn, and G.-Y. Kim, "A novel fingerprint recovery scheme using deep neural network-based learning," *Multimedia Tools and Applications*, vol. 80, no. 26–27, pp. 34121–34135, 2021, doi: 10.1007/s11042-020-09157-1.
[27] R. Gupta, M. Khari, D. Gupta, and R. G. Crespo, "Fingerprint image enhancement and reconstruction using the orientation and phase reconstruction," *Information Sciences*, vol. 530, pp. 201–218, Aug. 2020, doi: 10.1016/j.ins.2020.01.031.
[28] W. J. Wong and S.-H. Lai, "Multi-task CNN for restoring corrupted fingerprint images," *Pattern Recognition*, vol. 101, May 2020, doi: 10.1016/j.patcog.2020.107203.
[29] A. Dabouei, S. Soleymani, H. Kazemi, S. M. Iranmanesh, J. Dawson, and N. M. Nasrabadi, "ID preserving generative adversarial network for partial latent fingerprint reconstruction," in *2018 IEEE 9th International Conference on Biometrics Theory, Applications and Systems*, IEEE, Oct. 2018, pp. 1–10, doi: 10.1109/BTAS.2018.8698580.
[30] N. Singla, M. Kaur, and S. Sofat, "Hybrid framework for identifying partial latent fingerprints using minutiae points and pores," *Multimedia Tools and Applications*, vol. 81, no. 14, pp. 19525–19542, Jun. 2022, doi: 10.1007/s11042-021-11541-4.
[31] S. M. S. Hilles *et al.*, "Adaptive latent fingerprint image segmentation and matching using chan-vese technique based on EDTV model," in *2021 2nd International Conference on Smart Computing and Electronic Enterprise*, IEEE, Jun. 2021, pp. 2–7, doi: 10.1109/ICSCEE50312.2021.9497996.
[32] S. Gu, J. Feng, J. Lu, and J. Zhou, "Latent fingerprint registration via matching densely sampled points," *IEEE Transactions on Information Forensics and Security*, vol. 16, pp. 1231–1244, 2021, doi: 10.1109/TIFS.2020.3032041.
[33] U. U. Deshpande, V. S. Malemath, S. M. Patil, and S. V. Chaugule, "Automatic latent fingerprint identification system using scale and rotation invariant minutiae features," *International Journal of Information Technology*, vol. 14, no. 2, pp. 1025–1039, 2022, doi: 10.1007/s41870-020-00508-7.
[34] D.-L. Nguyen and A. K. Jain, "End-to-end pore extraction and matching in latent fingerprints: going beyond minutiae," *arXiv:1905.11472,* 2019.
[35] A. Manickam *et al.*, "Bio-medical and latent fingerprint enhancement and matching using advanced scalable soft computing models," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 10, pp. 3983–3995, Oct. 2019, doi: 10.1007/s12652-018-1152-1.
[36] J. Ezeobiejesi and B. Bhanu, "Patch based latent fingerprint matching using deep learning," in *2018 25th IEEE International Conference on Image Processing*, IEEE, Oct. 2018, pp. 2017–2021, doi: 10.1109/ICIP.2018.8451567.
[37] N. Kapoor, P. Moon, P. Pardeshi, and A. Badiye, "Introduction to fingerprints," in *Textbook of Forensic Science*, Singapore: Springer Nature Singapore, 2023, pp. 245–278, doi: 10.1007/978-981-99-1377-0_8.
[38] K. Cao and A. K. Jain, "Latent fingerprint recognition: role of texture template," in *2018 IEEE 9th International Conference on Biometrics Theory, Applications and Systems*, IEEE, Oct. 2018, pp. 1–9, doi: 10.1109/BTAS.2018.8698555.
[39] Q. Yin, J. Feng, J. Lu, and J. Zhou, "Orientation field estimation for latent fingerprints by exhaustive search of large database," in *2018 IEEE 9th International Conference on Biometrics Theory, Applications and Systems*, IEEE, Oct. 2018, pp. 1–9. doi: 10.1109/BTAS.2018.8698594.
[40] A. Malhotra, M. Vatsa, R. Singh, K. B. Morris, and A. Noore, "Multi-surface multi-technique (MUST) latent fingerprint database," *IEEE Transactions on Information Forensics and Security*, vol. 19, pp. 1041–1055, 2024, doi: 10.1109/TIFS.2023.3280742.
[41] M. Liu and P. Qian, "Automatic segmentation and enhancement of latent fingerprints using deep nested UNets," *IEEE Transactions on Information Forensics and Security*, vol. 16, pp. 1709–1719, 2021, doi: 10.1109/TIFS.2020.3039058.
[42] A. Sankaran, M. Vatsa, and R. Singh, "Multisensor optical and latent fingerprint database," *IEEE Access*, vol. 3, pp. 653–665, 2015, doi: 10.1109/ACCESS.2015.2428631.
[43] L. Premk, Z. Emersic, and T. Oblak, "Automatic latent fingerprint segmentation using convolutional neural networks," in *2021 44th International Convention on Information, Communication and Electronic Technology*, IEEE, Sep. 2021, pp. 1010–1014. doi: 10.23919/MIPRO52101.2021.9597100.

[44] R. Dhaneshwar and M. Kaur, "Latent fingerprinting: a review," in *Emerging Technologies in Data Mining and Information Security*, Springer, Singapore, 2021, pp. 45–54, doi: 10.1007/978-981-33-4367-2_5.

[45] D. V.-Ramirez *et al.*, "A review of fingerprint feature representations and their applications for latent fingerprint identification: trends and evaluation," *IEEE Access*, vol. 7, pp. 48484–48499, 2019, doi: 10.1109/ACCESS.2019.2909497.

[46] M. D. Garris, "Latent fingerprint training with NIST special database 27 and universal latent workstation," *tsapps.nist.gov*, 2001. [Online]. Available: https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=151537

[47] J. Khodadoust and A. M. Khodadoust, "Partial fingerprint identification for large databases," *Pattern Analysis and Applications*, vol. 21, no. 1, pp. 19–34, Feb. 2018, doi: 10.1007/s10044-017-0665-0.

[48] N. Martins, J. S. Silva, and A. Bernardino, "Fingerprint recognition in forensic scenarios," *Sensors*, vol. 24, no. 2, Jan. 2024, doi: 10.3390/s24020664.

[49] R. P. Sharma and S. Dey, "Fingerprint image quality assessment and scoring using minutiae centered local patches," *Journal of Electronic Imaging*, vol. 28, no. 01, 2019, doi: 10.1117/1.JEI.28.1.013016.

[50] D. Maio, D. Maltoni, R. Cappelli, J. L. Wayman, and A. K. Jain, "FVC2004: third fingerprint verification competition," in *Biometric Authentication-(ICBA 2004)*, Springer, Berlin, Heidelberg, 2004, pp. 1–7, doi: 10.1007/978-3-540-25948-0_1.


## BIOGRAPHIES OF AUTHORS

**Nandita Manchanda** is currently working as Assistant Professor at Chandigarh University, Mohali, India. She received an M.Tech degree in Computer Science from M.M University, Mullana, India, and currently pursuing a Ph.D. from Chandigarh University, Mohali, India. She has around 14 years of teaching experience. Her area of specialization is image processing, machine learning, and design & analysis of algorithms. She has published 2 book chapters and 8 papers in the reputed journals and conferences. She can be contacted at email: nandita.malik2721@gmail.com.

**Sanjay Singla** is Professor at Chandigarh University, Mohali, India. He received a Ph.D. degree in Computer Science from Maharishi Dayanand University, Rohtak, India served as Head of the Department at the Institute of Engineering and Technology, Baddal, India. He has almost 20 years of academic and research experience. He is an active member of the editorial board/reviewer in various reputed journals. He is the author or coauthor of more than 40 papers in international refereed journals and conference proceedings. His research interests include software testing, software engineering, image processing, machine learning and soft computing. He can be contacted at email: sanjay.e13538@cumail.in.

**Gopal Rathinam** is currently working as a Professor at University of Buraimi, Al Buraimi, Oman. He received a Ph.D. degree from Department of Information and communication Engineering, Anna University, India. He has served on many technical program committees and as reviewer in reputed journals like wireless personal communication, Springer. His research interests include span wireless sensor networks, malicious node detection, cooperative networks, and internet of things. He has a list of publications in reputed journals, editor for 2 Scopus indexed books, and published 8 book chapters. He can be contacted at email: gopal.r@uob.edu.om.