

**ARTICLE**

# A Study on Automatic Latent Fingerprint Identification System

**Uttam U Deshpande<sup>1\*</sup> V. S. Malemath<sup>2</sup>**

1. KLS Gogte Institute of Technology, Udyambag, Belagavi, Karnataka, India

2. KLE Dr. M.S. Sheshgiri College of Engineering and Technology, Udyambag, Belagavi, India

---

**ARTICLE INFO**

*Article history*

Received: 22 January 2022

Accepted: 23 February 2022

Published Online: 28 February 2022

*Keywords:*

Fingerprint identification system

NIST

Latent fingerprints

Forensics fingerprint database

---

**ABSTRACT**

Latent fingerprints are the unintentional impressions found at the crime scenes and are considered crucial evidence in criminal identification. Law enforcement and forensic agencies have been using latent fingerprints as testimony in courts. However, since the latent fingerprints are accidentally leftover on different surfaces, the lifted prints look inferior. Therefore, a tremendous amount of research is being carried out in automatic latent fingerprint identification to improve the overall fingerprint recognition performance. As a result, there is an ever-growing demand to develop reliable and robust systems. In this regard, we present a comprehensive literature review of the existing methods utilized in latent fingerprint acquisition, segmentation, quality assessment, enhancement, feature extraction, and matching steps. Later, we provide insight into different benchmark latent datasets available to perform research in this area. Our study highlights various research challenges and gaps by performing detailed analysis on the existing state-of-the-art segmentation, enhancement, extraction, and matching approaches to strengthen the research.

## 1. Introduction

Data handling capacity has increased as a result of technological improvements, allowing for more reliable personal authentication systems. In the various civil, legal system, and forensics, fingerprint matching technology is widely used. Rolled or slap fingerprints are used in in-person authentication. This method was recently used in popular civil applications like India's Aadhaar (UIDAI) project. Other law enforcement and criminal investigation include access-control systems, finance monitoring systems, border security systems, and forensic applications.

Human activities can be identified by his behavior and physical attributes. Among physiological (DNA, iris, face, fingerprints) and behavioral (typing pattern, gait, voice) biometrics<sup>[1]</sup>, the fingerprint is the most widely used in person recognition. This is due to their reliability, accessibility, uniqueness, low cost, and sensor and algorithm maturity. In crime investigation, forensic professionals consider fingerprint matching to be a more reliable and extensively employed technique. In most cases, a person's fingerprints do not change over time. Only if a person is exposed to cuts and wounds on the finger, whether intentionally or accidentally, can change occur. Apart from fin-

---

\*Corresponding Author:

Uttam U Deshpande,

KLS Gogte Institute of Technology, Udyambag, Belagavi, Karnataka, India;

Email: [uttamudeshpande@gmail.com](mailto:uttamudeshpande@gmail.com)

DOI: <https://doi.org/10.30564/jcsr.v4i1.4388>

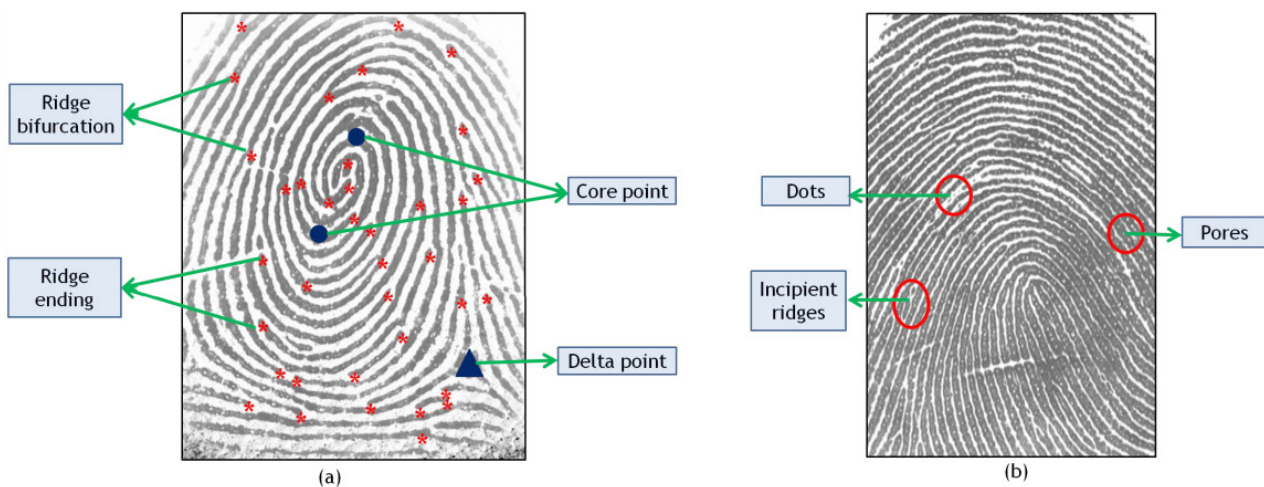
Copyright © 2022 by the author(s). Published by Bilingual Publishing Co. This is an open access article under the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) License. (<https://creativecommons.org/licenses/by-nc/4.0/>).

gerprint matching, palm-print, hand geometry, face, iris, and signature are also successfully deployed and used in personal identification. This is due to their individuality, universality, and invariability<sup>[2]</sup> properties.

In fingerprint applications, precision in fingerprint identification is critical. Fingerprint identification, validation, feature extraction, and classification are indeed stages of the fingerprint recognition system. A feature extraction stage is used to identify fingerprints, which is then followed by feature matching. The feature extraction approach used for identification is used to match extracted features. Fingerprint patterns are formed on the finger skin surface. Some of the features detected on fingerprints include ridge orientation-map, frequency-map, pores, dots, solitary points, and incipient. Aside from this, they contain various patterns such as Arch, Loop, and Whorl structures. These loops are then divided into nine different types of classifications<sup>[3]</sup>, namely right, left, double, the right pocket, left pocket, whorl, and mixed figure are examples. These traits are characterized as Level-1, Level-2, and Level-3<sup>[4]</sup>. Singular points, ridgeline flow, and ridge orientation form level-1 features. Level-2 features comprise minutiae. These are the details obtained from ridge bifurcations and endings. The minutiae make up the second level of features. The details gathered from ridge bifurcations and termination are as follows. Low-level information is included in Level-3 features. Level-3 elements include sweat pore locations and ridge forms<sup>[5]</sup>. Figure 1 depicts these characteristics. Ridge orientation map refers to the direction of ridge and valley structure. Classification, augmentation, and filtering are all done with these features. The ridge frequency map is used to filter fingerprint data and is reciprocal to the ridge distance in the direction perpendicular to the ridge orienta-

tion. Singular points are discontinuities in the orientation field. After fingerprint registration, these are employed in classification. Core points and Delta points are two types of singular points. The core point is the uppermost component of a curved ridge, while the delta point is the place where three ridge flows meet. Local discontinuities of the ridge structures are used to generate minutiae points. This is useful for verifying and authenticating people. During enrolment, a person's fingerprint is captured using ink or live scan methods<sup>[6]</sup>.

Latent fingerprints are accidentally left fingerprint impressions on objects, and the pressure of fingertip contact on objects varies. As a result, the data received from fingerprints are of poor quality and are directly not visible to human eyes. Overall, latent fingerprints pose different challenges compared to conventional fingerprint matching techniques. The results obtained may deviate from ideal to worst depending on the quality of the latent fingerprint. The fundamental reason for these outcomes is that minor details in latent patterns may be overlooked or corrupted by noise. Other obstacles include low image quality, poor texture, nonlinear distortion, inefficient matching techniques, and a readily available latent fingerprint database. The most basic prerequisite of latent fingerprint image enhancement is to develop a new image that contains more image information than the original image for assessment. This aids in the identification, verification, and matching process. In most cases, latent fingerprint pictures are of poor quality and polluted by noise. The success of latent fingerprint matching depends on the results obtained from the feature extraction stage. Choosing the right method of feature extraction is thus a difficult and complex problem. Capturing, pre-processing, fingerprint feature extraction, and matching are all phases in a typical latent fingerprint



**Figure 1.** Fingerprint features highlighting: (a) Level-1 and Level-2 features and (b) Level-3 features.

matching system.

Figure 2 depicts an example of latent fingerprint scans from the ELFT-EFS (Evaluation of Latent Fingerprint Technologies - Extended Feature Set) database [7]. In pre-processing step quality of the image is enhanced. Hence, ridge quality enhancement is done followed by segmentation to remove background noise from the ridge-like patterns. The feature extraction step involves the extraction of Level-1, Level-2, Level-3, and extended fingerprint features from the latent image. Either specific or combination of these features is used for uniquely identifying latent fingerprints. In the matching step, the query fingerprint template is matched with the database to identify a person. Latent fingerprint identification systems can be semi-automated or fully automated. These techniques pose various challenges.

### A. ACE-V Procedure

An automated fingerprint system can be created by following a set of standard methods for identifying latent fingerprint features and then having an expert examine the fingerprints manually to identify a person. The ACE-V (Analysis, Comparison, Evaluation, and Verification) technique is followed to examine the latent fingerprint manually [8]. The ACE-V approach is a consistent and structured method for comparing ridge impressions. ACE-V methodology is formed from four sequential phases. Namely Analysis, Comparison, Evaluation, and Verification. Knowledge gained after inspection of every step is applied in subsequent stages.

Manual observation of latent fingerprints is prone to inconsistency due to human participation [9]. This causes ACE-V procedure errors. This is a time-consuming, difficult process that can result in a biased outcome. These drawbacks can be overcome by automating the entire procedure. In circumstances where a large number of

latent fingerprint needs to be matched automated latent fingerprint matching system can assist the experts. An Automatic Fingerprint Identification System (AFIS) is in its initial stages. “Lights-out” matching system [10] is in its development stage. For developing automated systems, researchers have to overcome several research challenges. Some of these research challenges are classified as resource-based and algorithmic-based. Efforts are being made to completely automate the process. But developing a system that has the efficiency of a human eye, knowledge, and decision-making ability is not an easy task.

The main objective of this review study is to introduce the existing latent fingerprint matching algorithms, and highlight their advantages, limitations against the available state-of-art algorithms. First, we analyze the existing state-of-the-art latent fingerprint segmentation, enhancement, feature extraction, and matching methods. Next, we bring out important observations by emphasizing their salient features and research gaps in the methods proposed by various researchers. Later, we discuss the publicly available benchmark latent datasets helpful in carrying out research. Finally, the study concludes by highlighting future research opportunities available at different latent fingerprint identification system stages. Section 2 further talks over about the steps involved in an automatic latent fingerprint matching system in detail. Section 3 discusses the techniques for segmenting the latent image and specifies the various preprocessing steps involved in latent image processing. The quality assessment and enhancement methods available for latent image feature extraction are highlighted in section 4. Section 5 explains different feature extraction techniques practised. Latent fingerprint matching methods are introduced in section 6. Section 7 lists publicly available latent fingerprint databases. Section 8 outlines the concerns and challenges in latent fingerprint matching, while Section 9 wraps up the study findings and offers some suggestions for future research.

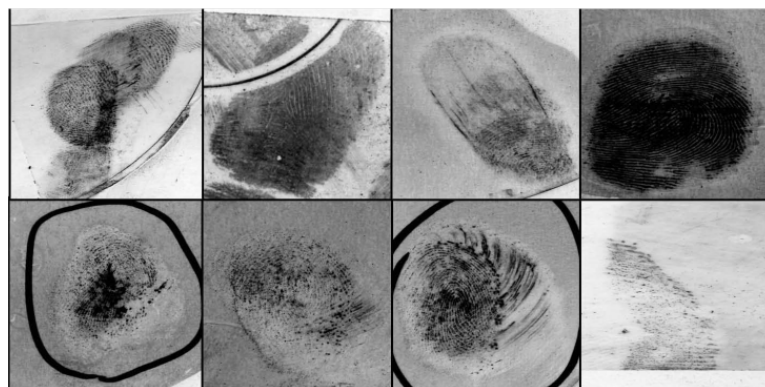


Figure 2. Different latent fingerprint images.

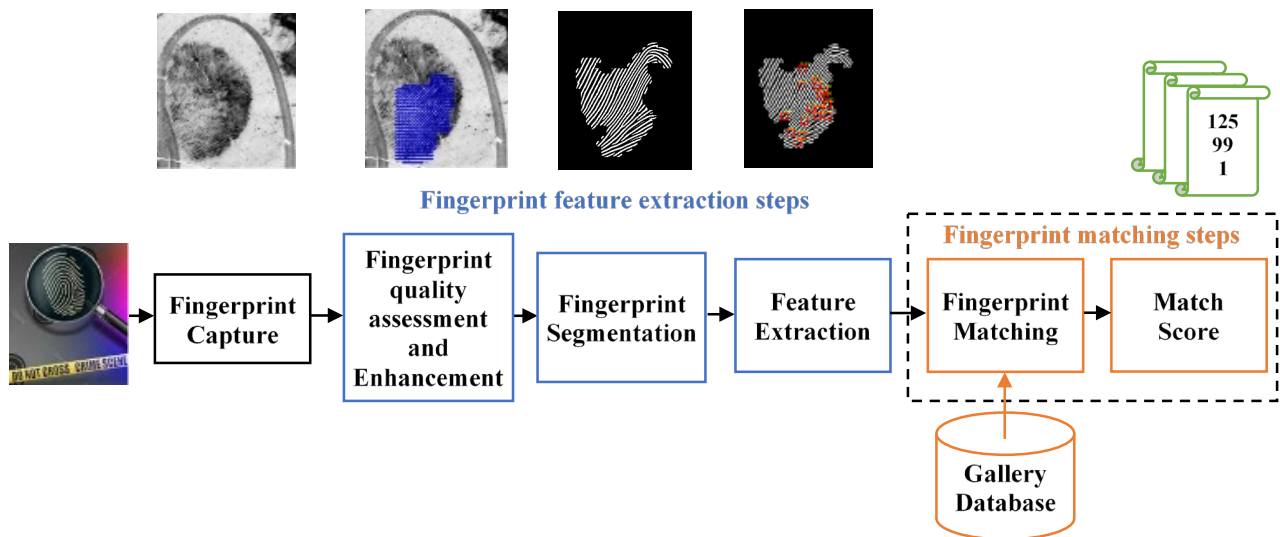


Figure 3. Automated latent fingerprint recognition system.

## 2. Automatic Latent Fingerprint Identification System

The fundamental goal of an automatic latent fingerprint recognition system, as previously said, is to reduce human participation. An automated matching system should be designed to make it deterministic and to overcome the problem of subjective inconsistency. It should also be designed to reduce the matching time. The Integrated Automatic Fingerprint Identification System (IAFIS) is capable of holding 70 million criminal fingerprint subjects from different regions of the world, including 31 million civilian fingerprint subjects, 73,000 known and suspected terrorist fingerprints collected by the US law enforcement agencies<sup>[11]</sup>. The average response time for 73K criminal fingerprints is about 27 minutes. In comparison, the response time reported in 2010 for 61 million civil ten-print submissions takes about an hour and 12 minutes. In comparison to manual matching, an automated latent fingerprint matching system should be able to give better, faster, and more deterministic results. The overall process of an automatic latent fingerprint matching system is depicted in Figure 3. Pre-processing, quality assessment as well as enhancement, feature extraction, and matching steps are all included. To identify and compare latent fingerprints, feature extraction is critical. An automatic latent fingerprint matching system typically receives a digitally scanned or camera-acquired latent print as input<sup>[11]</sup>. With the advancement in high-performance GPUs, it is now possible to develop Deep Learning-based Convolution Neural Networks (DCNN) in several medical diagnostics applications<sup>[12]</sup> including latent fingerprints. With hardware optimization, these DCNN algorithms can produce

better results in lesser time. Digitized fingerprint data can help to transmit the data over remote systems for further processing and to perform recognition tasks. This poses serious concerns about a person's privacy information<sup>[13]</sup>. Face recognition system based on digitized data has proved that a person's identity can be achieved securely<sup>[14]</sup>.

## 3. Pre-processing and Segmentation

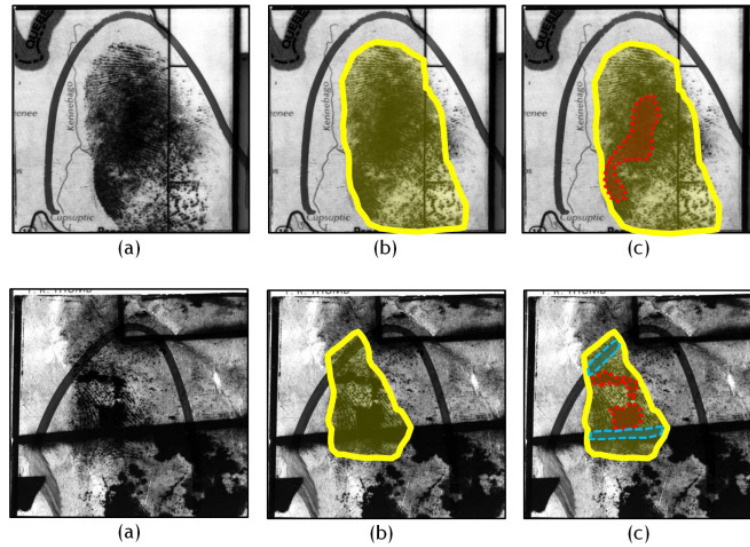
Preprocessing is done on a digital image to enhance the features of the fingerprint by suppressing unwanted noise and image features. The following 5 major techniques are widely used in pre-processing.

- The process of transforming a grayscale image to a binary image is known as "binarization".
- To lessen the darkness of ridgelines, image thinning is utilized<sup>[15]</sup>.
- Unraveling foreground fingerprint features from its background noise is called "Segmentation".
- The histogram equalization technique is used to improve contrast by boosting image intensities. Using this technology, low-quality latent fingerprint scans are upgraded to an acceptable level.
- Smoothing techniques are used to decrease noise in an image or to prepare it for subsequent processing.

Poor discrimination of information features and low-quality boundary foreground make the segmentation step a challenging one. Latent fingerprint segmentation is a process of marking the outline boundary, and is shown in Figure 4 (b)-(c) shows smudges and noises marked inside the boundary along with the outer boundary of latent fingerprint 4(a).

Because segmentation is such an important stage, the major goal should be to reliably mark all foreground re-





**Figure 4.** Segmented latent fingerprint images. (a) Original image, (b) segmentation done on the outside boundary, and (c) segmenting the outline of latent fingerprint (yellow lines) with simultaneous marking of structured noise (blue lines) and smudgy region.

gions while decreasing background noise as much as feasible. Research contributions made by several researchers can be classified as Non-convolution network (non-ConvNet) patch-based and convolution network (ConvNet) patch-based approaches.

### A. Non-ConvNet patch-based approaches

Choi et al. <sup>[16]</sup> constructed orientation and frequency maps to use as reference points in evaluating latent patches in 2012. This dictionary lookup map was used to classify each patch into two classes. The classified patches-based dictionary technique was carried out in 2014 by Cao et al. <sup>[17]</sup>. In 2015, Ruangsakul et al. <sup>[18]</sup> proposed a Fourier sub-band method of segmentation. It further needs to be post-processed to fill gaps and eliminate islands. Segmented output quality depends on dictionary quality and needs post-processing to make the masks smooth. Texture information was utilized by Liu et al. <sup>[19]</sup> in 2016 to develop linear density on a set of line segments. But this requires further post-processing. Features used in most of the methods are “handcrafted” and rely on post-processing techniques. Latent fingerprint cropping using deep neural networks has also been implemented.

### B. ConvNet patch-based approaches

Zhu et al. <sup>[20]</sup> used classification of patches using neural network framework in 2017. Ezeobijesi et al. <sup>[21]</sup> used a stack of restricted Boltzmann machines in the year 2017. Apart from pre-processing techniques suggested to obtain

thinned ridge patterns, various post-processing methodologies are listed to eliminate unwanted or noisy ridge patterns present after ridge thinning. It is very important to eliminate such unwanted ridge patterns as their presence contributes to false minutiae. In 2018, Dinh-Luan Nguyen et al. <sup>[22]</sup> proposed a fully automated convolution neural network segmentation method SegFinNet. This combines a fully convolutional neural network and a detection-based approach to process the entire input latent image in one shot instead of using latent patches.

Recently in 2019, Asif Iqbal Khan et al. <sup>[23]</sup> proposed a CNN approach for classifying fingerprint patches. They trained fingerprint patches with false patch elimination using the Stochastic Gradient Descent (SGD) technique. False match remover learns “most of the neighbors” to delete faulty or wrongly classified patches to construct the Region of Interest (ROI). An experiment conducted on the IIIT-D database achieves 5.2% MDR and 13.8% FDR respectively. They observed that the proposed patch-based segmentation system consumed more processing time. Some state-of-art segmentation algorithms are listed in Table 1. On the NIST Special Database-27 <sup>[24]</sup> and West Virginia University (WVU) latent databases <sup>[25]</sup>, “SegFinNet,” an automated segmentation method presented by Dinh-Luan Nguyen et al. <sup>[22]</sup>, surpasses human latent markup and state-of-the-art latent segmentation algorithms <sup>[16,17,22,23]</sup>. Table 1 summarises the significant contributions made by several scholars to fingerprint pre-processing and segmentation.

#### 4. Quality Assessment and Enhancement

Before performing extraction, ridge flow enhancement of a latent fingerprint is an extremely important and necessary procedure. To increase the quality of a latent fingerprint, the quality of the latent image is analyzed in this step, and enhancement is performed based on the assessment. Assessed data are used to determine whether the bare minimum of data is present to make a valid confidence match. FTE (Failure-To-Enroll) or FTR (Failure-To-Register) latent fingerprints that do not meet the criterion will be discarded<sup>[6]</sup>. These have no bearing on the precision of the matching system's performance. Overall, the quality enhancement procedure reduces noise from a latent fingerprint image and improves its quality. This will aid the feature extraction procedure in completing its duty. Hicklin et al.<sup>[26]</sup> conducted the first investigation on the quality of fingerprint features in 2007. In 2008, Karimi and Kuo<sup>[27]</sup> presented a Gabor filter-based approach for latent fingerprint picture segmentation and enhancement. Yoon et al.<sup>[28]</sup> introduced a technique for manually indicating singular points and Regions of Interest (ROI) for latent fingerprint enhancement in 2012. Experiments carried out on NIST SD27 datasets influenced the orientation estimation and match accuracy. To boost fingerprint enhancement performance, they developed a more robust and improved ridge orientation estimation algorithm. They went on to build "lights-out" mode devices to assess the quality of a latent fingerprint. Based on the quality of the input latent image, this system may anticipate whether or not complete automatic identification is possible. To determine the latent quality, the authors looked into ridge quality, high-quality minutia patches, and a reference point. Feng et al.<sup>[29]</sup> presented a relaxation labeling technique in 2013 to overcome the problem of matched latent fingerprint orientation. The unique fingerprint orientation field estimation algorithm was developed using prior information of fingerprint structure. Set of genuine patches that aid in the acquisition of prior knowledge about fingerprints. In 2014, Cao et al.<sup>[17]</sup> developed a method for improving fingerprints using a dictionary of high-quality ridges in 2014. To recreate the poor latent, the dictionary's same ridge patterns (orientation and frequency) were used. Ezhilmaran and Adhiyaman<sup>[30]</sup> explored contrast enhancement using an intuitionistic Type-2 fuzzy set later in 2016. They also devised an intuitive Type-2 fuzzy entropy algorithm for latent fingerprint edge detection. In 2018, Jian Li et al.<sup>[31]</sup> introduced "FingerNet", a CNN-based network. In FingerNet, they created an encoding convolutional component and two decoding deconvolutional components. These blocks serve as augmentation and orientation

branches. In 2019, I. Joshi et al.<sup>[32]</sup> proposed the use of a trained enhancer and discriminator in a Generative Adversarial Network (GAN) for ridge structure amplification. The main research contribution made by various researchers in quality assessment and enhancement is tabulated in Table 1. State-of-art algorithm<sup>[17,29,31]</sup> provides better enhancement results compared to the research contributions discussed above.

#### 5. Latent Fingerprint Feature Extraction

Fingerprint characteristics are the most exact representation of any data in a fingerprint matching system. To maintain the uniqueness of fingerprint matching systems, particularly robust feature representation methods are required. In latent fingerprint matching, the feature extraction technique is the most important stage. Due to the low quality of latent pictures, it is critical to capture all aspects of the latent fingerprints to match them efficiently. Extraction of latent fingerprint features is a complex technique. Sankaran et al.<sup>[33]</sup> suggested an automated technique for extracting latent fingerprint minutiae. Using an unsupervised feature learning technique, the minutiae and non-minutiae patches are discriminated from high-quality images. Later, they did a comprehensive study in which he described the advantages of the automated hierarchical fusion approach and the simultaneous latent fingerprint database. Paulino<sup>[34]</sup> offered manually marked minutiae with mechanically retrieved minutiae for latent to full fingerprint matching to improve the accuracy of the NIST SD27 database. These characteristics are integrated to perform Scale Invariant Feature Transformation (SIFT) on a large portion of the foundation database while retaining latent matching accuracy via indexing. The following fingerprint traits<sup>[6]</sup> are the most often employed in fingerprint recognition because of their limited data content and low quality of ridge information:

- Minutiae points - ridge termination and bifurcation.
- The singularities - Arch type (no singularity), Loop and Tented arch (one core and one delta), whorl and loop (two cores and two deltas).
- Region Of Interest (ROI) - It is a closed area that is limited at the external most trim of the latent.
- Ridge Orientation field - Represent the global structure of fingerprints.

The fingerprint feature can be classified into three levels: Level 1, Level 2, and Level 3. In comparison to Level 2 or Level 3 features, the Level 1 feature is the most extensively employed in latent fingerprint identification systems. For core point extraction of latent fingerprints, Su and Srihari<sup>[35]</sup> utilized a Gaussian process. Prior joint Gaussian distribution and regression methods were used

to derive the singular points and location, respectively.

Yao Tang and fellow researchers proposed the fully convolutional neural network (CNN) approach<sup>[36]</sup>. In this case, tiny points are fed into a CNN, which reclassifies them and calculates their orientations. Later, they created “FingerNet” a deep convolutional network that incorporates domain knowledge with deep learning representation. Traditional latent fingerprint feature extraction approaches that were tested on rolling and slap fingerprints were modified and combined into a basic unified network in a completely convolutional manner. On various minutiae orientation and distance settings, they got Precision, Recall, and F1 scores. Darlow et al.<sup>[37]</sup> proposed the “Minutiae Extraction Network (MENet)” Deep-Convolutional Neural Network in 2017 to learn a data-driven representation of minutia points. MENet is trained on a huge library to reduce manual data labeling and boost robustness. “MinutiaeNet”, an automated, robust minutiae extractor, was presented by Nguyen et al.<sup>[22]</sup> in 2018. MinutiaeNet is a domain knowledge-based deep network representation. Nguyen et al. created “CoarseNet”, a residual learning-based model, and “FineNet”, an inception-residual network, using domain knowledge. Without a specified threshold, CoarseNet provides an automatic position and orientation of minutiae. FineNet is a patch-focused classifier that helps CoarseNet find and generate final findings. In 2021, U. U. Deshpande et al.<sup>[38]</sup> introduced a CNN-based automatic minutiae extractor using a dynamic thresholding filtration algorithm to suppress false minutiae points. Researchers’ contributions are summarized in Table 1. In comparison to the other algorithms, the state-of-the-art<sup>[22,34,36,38]</sup> algorithms perform better.

## 6. Latent Fingerprint Matching

The primary goal of a latent fingerprint matching procedure is to determine the degree of resemblance between the fingerprint under inquiry and the gallery fingerprint. The matching algorithm should try and increase the matching accuracy while decreasing dissimilarities.

Latent fingerprint matching can be classified into three families based on fingerprint features:

- **Correlation-based matching:** The similarity of two fingerprint images is computed by determining the correlation between corresponding pixels at different alignments.
- **Minutiae-based matching:** This is the most well-known and widely used feature. The minutiae are extracted from the two fingerprints and placed on a two-dimensional plane. Minutia-based matching entails determining the relationship between the minutiae format and the information entered into pairs.
- **Non-Minutiae feature-based matching:** Minuti-

ae extraction is difficult in low-quality fingerprint photos. Different traits, such as ridge shape, may be isolated from more reliable minutiae. However, their distinctiveness and consistency are generally lesser.

Jain et al.<sup>[10]</sup> presented minutiae points, unique points, ridge quality map, ridge flow map, ridge wavelength map, and skeleton characteristics for latent fingerprint matching. Sankaran et al.<sup>[33]</sup> created fusion and context switching frameworks for latent-to-latent fingerprint matching. Paulino et al.<sup>[34]</sup> demonstrated how to align two sets of minutiae, create correspondences, and generate a similarity score using a descriptor-based Hough transform. Liu et al.<sup>[39]</sup> presented feedback-based latent fingerprint matching from exemplar print. This is used in candidate list recovery from the database and score level-based matching.

Miguel Angel Medina-Pérez et al.<sup>[40]</sup> presented a clustering technique based on minutiae descriptors to improve MCC, M triplets, and nearby minutiae-based descriptors. The “Latent Minutiae Similarity” (LMS), “Clustered Latent Minutiae Pattern” (CLMP), and “Ratio of Minutiae Triangles” (RMT) algorithms, developed by U. U. Deshpande et al.<sup>[41]</sup>, are alignment-free and rotation/scale-invariant. They clustered minutiae structures around a reference minutia and generated minutiae invariant feature vectors to develop discriminative feature vectors needed for fingerprint matching.

In 2018, Cao et al.<sup>[42]</sup> achieved automated latent fingerprint detection using the CNN (ConvNets) model. To estimate ridge flow, extract minutiae points, and build two minutiae templates as well as a texture template, ConvNets was employed. Furthermore, they proposed an improved algorithm that creates Virtual minutiae to account for missing minutiae and compensate for good minutiae points. Different texture templates are provided by minutiae descriptors created for virtual minutiae. The technique enhanced the distinctness of simulated minutiae descriptors by classifying the patches from the original fingerprints. To build numerous texture templates, they used hierarchical graph matching, which increased the matching accuracy. Ezeobiejese et al.<sup>[43]</sup> employed deep networks to build a patch-based latent fingerprint representation and matching in 2018. To learn the finest minutiae representations from picture patches, deep networks were used. Ezeobiejese et al. calculated the similarity scores between latent and reference fingerprint patches using a distance method. Combining minutiae patch and similarity scores yielded the final matching score.

Nguyen et al.<sup>[44]</sup> created an end-to-end automated latent AFIS using ridge pores in 2019. Using a manual graph matching approach, the system determines the relationship between pore and minutiae features.

Recently in 2020, U. U. Deshpande et al.<sup>[45]</sup> proposed

**Table 1.** Published works at different stages of latent fingerprint matching.

STEP	STUDY	METHOD	DATABASE	RESULTS
SEGMENTATION	Choi et al. <sup>[16]</sup> , 2012.	The frequency of ridges and the orientation of the patches. Relies on the quality of the supplied image and the orientation estimation. <b>Drawbacks:</b> Fingerprint quality and orientation field estimates determine the performance.	32K NIST SD27 and WVU Background fingerprints	Matching: With a Commercial of The Shelf (COTS) ten-print matcher, 16.28 % on NIST SD27 and 35.1 % on WVU were achieved.
	Cao et al. <sup>[17]</sup> , 2014.	Patch classification based on ridge flow enhancement of learned dictionary and smoothed mask using convex hull. <b>Drawbacks:</b> A fully automatic segmentation system that does not require manual markup. The method depends on the learned dictionary and convex hull.	NIST SD27 and WVU. Background: 32K images	Matching: 61.24% on NIST SD27 and 70.16% with COTS matcher
	Dinh-Luan Nguyen et al. <sup>[22]</sup> , 2018.	Automatic segmentation (SegFinNet) based on Full CNN (FCN) and detection-based fusion. Uses Non-patch, Non-warp ROI, Visual attention, and Voting masks techniques. <b>Drawbacks:</b> A non-patch-based neural network operation on the complete image.	NIST SD27, WVU, Forensic database. Background: 100K images	Matching: With a COTS matcher, 70.8 % on NIST SD27 and 71.3 % on WVU; Matching: 12.6% on NIST SD27 and 28.9% on WVU with Verifinger SDK 6.3 on 27K images
	Asif Iqbal Khan et al. <sup>[23]</sup> , 2019.	Patch foreground and background classifier based on convolutional neural networks (CNN). <b>Drawbacks:</b> Patch-based processing consumes a lot of time.	IIIT-D latent Fingerprints.	MDR <sup>(+)</sup> : 5.2%, FDR <sup>(-)</sup> : 13.8%. Match accuracy was not reported.
QUALITY ASSESSMENT AND ENHANCEMENT	Yoon et al. <sup>[29]</sup> , 2012.	Short-Time Fourier Transforms (STFT) + RANSAC (randomized RANdom SAmple Consensus) on manually marked ROI <b>Drawbacks:</b> A human expert or AFIS does the quality assessment.	NIST SD27 and WVU DB	Rejection of 50% on poor quality latent information and improved rank-100 identification accuracy from 69 to 86 %.
	Cao et al. <sup>[17]</sup> , 2014.	Ridge flow improvement approach based on a dictionary. The reconstructed fingerprint is computed, and the orientation and frequency elements are utilized to modify Gabor filters for fingerprint enhancement. <b>Drawbacks:</b> Fully automated segmentation with no manual marking is required.	NIST SD27, WVU	Rank-1 identification accuracy of 61% (NIST SD27) and 70% (WVU)
	Jian Li et al. <sup>[31]</sup> , 2018.	To extract fingerprint characteristics, use a convolution layer. For improvement (removing structured noise) and orientation operations, two distinct deconvolution layers are used (multi-task learning). <b>Drawbacks:</b> When background noise is present, performance suffers.	NIST SD27	55% Rank-20 accuracy
FEATURE EXTRACTION	Paulino et al. <sup>[34]</sup> , 2013.	Minutiae extraction and MCC descriptor-based indexing of minutiae triplets using Ridge improvement <b>Drawbacks:</b> An automated extractor was used to extract minutiae characteristics. Manually annotated minutiae (Level 2) characteristics to aid with fingerprint matching and alignment.	NIST SD27	Identification accuracy of 33% for the Rank-10 order.

(Continues)



Table 1 (Continued)

STEP	STUDY	METHOD	DATABASE	RESULTS
FEATURE EXTRACTION	Tang et al. <sup>[36]</sup> , 2017.	To distinguish between minutiae and non-minutia patches, a CNN algorithm learns the fingerprint pixels. The minutia position is extracted using location regression. <b>Drawbacks:</b> Reliable minutiae (level 2 characteristics) that have not been segmented or enhanced. Candidate patches with minor details are excluded by the hard threshold, and candidate patches are generated and classified by the same network.	NIST SD27	Precision - 63%, Recall - 63.2%, F1 score - 0.631
	Dinh-Luan Nguyen et al. <sup>[22]</sup> , 2018.	Domain knowledge and deep network representation combined (MinutiaeNet). CoarseNet is built using domain knowledge and residual learning, while FineNet is built using an inception-residual network. <b>Drawbacks:</b> Extraction of minutiae is done automatically. Genuine minutiae candidate areas are deleted by adaptive threshold filtration with a static threshold value.	NIST SD27	Precision - 71.2%, Recall - 75.7%, F1 score-0.734
	U. U. Deshpande et al. <sup>[38]</sup> , 2021.	A residual learning framework to automatically segment, enhance, and extract minutiae features. A dynamic thresholding filtration algorithm to eliminate false minutiae points. <b>Drawbacks:</b> The suggested model struggled to detect actual minutiae near the fingerprint boundary or failed to identify fake minutiae.	NIST SD27	Precision-86.67%, Recall -92.85%, F1 score-0.896.
MATCHING	M. A. M. Perez et al. <sup>[40]</sup> , 2016.	Clustering algorithm to improve Cylinder-Codes, m-triplets, neighboring minutiae-based descriptor. <b>Drawbacks:</b> The minutiae descriptors have no impact on the minutiae cluster.	NISTSD27	Rank-1 identification of Cylinder-Codes was 68.6%, m-triplets was 68.2%, and nearby minutiae-based descriptor was 64%.
	U. U. Deshpande et al. <sup>[41]</sup> , 2021.	Alignment-free and rotation/scale-invariant LMS, CLMP, and RMT algorithms. <b>Drawbacks:</b> The fingerprint quality threshold has to be manually set. It requires a minimum of 8 minutiae neighbors.	NISTSD27	Rank-1 identification of LMS - 88.8%, CLMP - 93.80%, and RMT - 86.82%.
	K. Cao et al. <sup>[42]</sup> , 2018.	For latent representation, ConvNets use two minutiae templates and one texture template. Virtual minutiae creation has been included to compensate for missing minutiae. <b>Drawbacks:</b> Using virtual minutiae, ConvNets were used to improve minutiae and extract minutiae descriptors.	NISTSD27	Rank-1 identification accuracy of 68.2%.
	U. U. Deshpande et al. <sup>[45]</sup> , 2020.	CNN based End-to-End matching model (CNNAI) developed by integrating it with Minu-ExtractNet <sup>[38]</sup> model. <b>Drawbacks:</b> Matching accuracy highly depends on the trained model.	NISTSD27	Rank-1 identification accuracy of 84.5%.

MDR<sup>(+)</sup>: Missed Detection Rate, FDR<sup>(-)</sup>: False Detection Rate.

“Combination of the Nearest Neighbor Arrangement Indexing (CNNAI)”, an end-to-end Convolution Neural Network (CNN) matching model. To detect fingerprints, this approach uses a local minutiae representation. They integrated the CNNAI matching model with the previously established Minu-ExtractNet<sup>[38]</sup> to demonstrate its potential to provide effective match results without human involvement in an end-to-end framework. Table 1 highlights the important features of proposed latent fingerprint matching algorithms. It can be observed that the state-of-art matching algorithm<sup>[40-42,45]</sup> performs better than other listed algorithms. Table 2 provides the details of the publicly available fingerprint databases.

## 7. Latent Fingerprint Databases

The lack of a publicly accessible public latent fingerprint database is a stumbling block to further study in this field.

- Card ink print, live scan fingerprint, multi-resolution fingerprint, multi-sensor fingerprint, and full fingerprint techniques are used to construct databases that are then made available to the public, among other issues. Print, live scan fingerprint, multi-resolution fingerprint, multi-sensor fingerprint, and full fingerprint techniques are used to create databases that are then made available to the public.
- Capturing or collecting latent fingerprints is done by professionals. The unavailability of professionals makes this process time-consuming and expensive.
- Very few cost-effective techniques are available for lifting latent fingerprints.
- Simulating latent fingerprints in real-world settings is a difficult task. This is because latent fingerprints acquired at crime scenes will have a wide range of qualities. Creating databases with enough diversity by combining numerous sensors, diverse backdrops,

and multiple sessions is a time-consuming procedure.

Table 2 lists the public databases that can be used for research purposes. The WVU multimodal<sup>[25]</sup> database is a multi-session live scan fingerprint database. Tsinghua OLF<sup>[46]</sup>, NIST SD-27A<sup>[24]</sup>, IIIT-D SLF<sup>[47]</sup>, IIIT-D latent fingerprint database<sup>[47]</sup>, and IIIT-D MOLF (Multisensory Optical and Latent Fingerprint) Database<sup>[47]</sup> are some of the databases available. Databases are latent databases that have been collected several times with various backgrounds and have distinct properties.

## 8. Summary

There are many issues and challenges faced in latent fingerprint matching systems. These challenges are categorized as resource-based and algorithmic-based.

**Resource-based:** As discussed in the previous section, the lack of available professional experts and publicly available databases form a major issue in latent fingerprint matching. Although very fewer numbers of trained experts are available; error-free matching is a challenging task. Similarly, creating a special database with sufficient variability in latent fingerprints poses many questions.

**Algorithmic based:** Generally, latent fingerprint images are of poor quality. This is due to uneven pressure on the object, loss of information while lifting the fingerprint, or overlapped fingerprints. If proper procedures are not followed it may lead to spoiling of the complete matching system. Hence, appropriate pre-processing techniques are needed to obtain clear fingerprint features which intern improve the overall quality of the image.

Another major challenge in the fingerprint matching method is to tackle the large latent fingerprint database within a reasonable time. A detailed study on recent research contributions is highlighted after studying each stage. From the observations, it can be seen that the re-

**Table 2.** Fingerprint databases are available in public.

Capture type	Database	Classes	Images	Characteristics
Live-scan	WVU multimodal <sup>[25]</sup>	272	7219	<b>Capturing method:</b> CrossMatch, Precise Biometrics, SecuGen sensors at 500 dpi.
Latent	NIST SD-27A <sup>[24]</sup>	258	258	Manually annotated latent to exemplar fingerprint matching at 500 PPI and 1000 PPI respectively.
	Tsinghua OLF <sup>[46]</sup>	12	100	Overlapped latent fingerprints.
	IIIT-D SLF <sup>[47]</sup>	180	420	Manually annotated simultaneous slap latent fingerprints captured at 500 PPI.
	IIIT-D Latent Fingerprint <sup>[47]</sup>	150	1241	Latent to latent slap fingerprints with 500 PPI captured using a high-resolution camera.
	IIIT-D MOLF <sup>[47]</sup>	1000	19200	Manually annotated dap, slap, latent, and simultaneous latent fingerprints.

search is in its early phase of every stage and there is a large scope for research contribution in the respective fields. From the results, it can be seen that the manually annotated semi-automatic technique can achieve a maximum matching accuracy of 74% on the NIST SD-27 database. Whereas, End-to-End automatic fingerprint matching system produced the highest 84.5% Rank-1 identification accuracy. Hence, a fully automatic latent fingerprint matching system can significantly contribute to civil, law enforcement, and forensic applications.

## 9. Conclusions and Future Work

This survey provides detailed information on available latent fingerprint recognition methods. It also describes the issue and challenges of latent fingerprints. Both manual matching and the automated system based on latent fingerprint matching are discussed. Their merits and demerits are pointed out to develop an improved automated matching system. Studies reveal that automatic latent fingerprint identification technology is still in its nascent stage and there is a vast scope for research contribution in different fields of latent fingerprint matching. Moreover, issues with available resources and algorithms have led to open challenges for future researchers. The primary objective of this paper is to introduce the existing latent fingerprint matching algorithms, highlight their advantages and limitations against the available state-of-art algorithms. Finally, the paper concludes by highlighting future research opportunities available at different stages of the latent fingerprint identification system.

## Conflict of Interest

The authors declare no conflict of interest.

## References

- [1] Integrated pattern recognition and biometrics lab, West Virginia University.
- [2] Hawthorne, M.R., 2009. Fingerprints analysis and understanding. CRC Press, Taylor and Francis Group, Boca Raton, London, New York.
- [3] Jain, A.K., Flynn, P., Ross, A.A., 2007. Handbook of biometrics. Springer Science and Business Media, New York.
- [4] Kawagoe, M., Tojo, A., 1984. Fingerprint pattern classification. *Pattern Recognition*. 17(3), 295-303.
- [5] Sankaran, A., Vatsa, M., Singh, R., 1984. Latent fingerprint matching: A survey. *IEEE Access*. 2(2014), 982-1004.
- [6] Maltoni, D., Maio, D., Jain, A.K., et al., 2009. Handbook of Fingerprint Recognition. 2nd ed. New York, NY, USA: Springer-Verlag.
- [7] Evaluation of Latent Fingerprint Technologies. [Online] Available: <http://www.nist.gov/itl/iad/ig/latent.cfm>. (Accessed Oct. 24, 2013).
- [8] Ashbaugh, D., 1999. Quantitative-Qualitative Friction Ridge Analysis: An Introduction to Basic and Advanced Ridgeology. Boca Raton, FL, USA: CRC Press. pp. 134-135.
- [9] Ulery, B.T., Hicklin, R.A., Buscaglia, J., et al., 2011. Accuracy and reliability of forensic latent fingerprint decisions. *Proc. Nat. Acad. Sci. USA*. 108(19), 7733-7738.
- [10] Jain, A.K., Feng, J., Jan. 2011. Latent fingerprint matching. *IEEE Trans. Pattern Anal. Mach. Intell.* 33(1), 88-100.
- [11] Fact Sheet, 2013. Integrated Automated Fingerprint Identification System.
- [12] Shrestha, H., Dhasarathan, C., Kumar M., et al., 2022. A Deep Learning Based Convolution Neural Network-DCNN Approach to Detect Brain Tumor. In: Gupta G., Wang L., Yadav A., Rana P., Wang Z. (eds) Proceedings of Academia-Industry Consortium for Data Science. *Advances in Intelligent Systems and Computing*, vol 1411. Springer, Singapore. DOI: [https://doi.org/10.1007/978-981-16-6887-6\\_11](https://doi.org/10.1007/978-981-16-6887-6_11).
- [13] Bhardwaj, A., Mohamed, A., Kumar, M., 2021. Real-time Privacy-Preserving Framework for COVID-19 Contact Tracing. *Computers, Materials and Continua*. 70. DOI: <https://doi.org/10.32604/cmc.2022.018736>.
- [14] Singh, S., Chintalacheruvu, S.C.K., Garg, S., et al., 2021. Efficient Face Identification and Authentication Tool for Biometric Attendance System. 2021 8th International Conference on Signal Processing and Integrated Networks (SPIN). pp. 379-383. DOI: <https://doi.org/10.1109/SPIN52536.2021.9565990>.
- [15] Diefenderfer, G.T., 2006. Fingerprint Recognition. DTIC Document, Naval Post Graduate School, Monterey, California.
- [16] Choi, H., Boaventura, M., Boaventura, I.A., et al., 2012. Automatic segmentation of latent fingerprints. In *IEEE International Conference on Biometrics: Theory, Applications and Systems*. pp. 303-310.
- [17] Cao, K., Liu, E., Jain, A.K., 2014. Segmentation and enhancement of latent fingerprints: A coarse to fine ridge structure dictionary. in *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 36(9), 1847-1859.
- [18] Ruangsakul, P., Areekul, V., Phromsuthirak, K., et al., 2015. Latent fingerprints segmentation based on rearranged fourier subbands. in *IEEE International*

- Conference on Biometrics. pp. 371-378.
- [19] Liu, S., Liu, M., Yang, Z., 2016. Latent fingerprint segmentation based on linear density. In IEEE International Conference on Biometrics. pp. 1-6.
- [20] Zhu, Y., Yin, X., Jia, X., et al., 2017. Latent fingerprint segmentation based on convolutional neural networks,” in IEEE Workshop on Information Forensics and Security. pp. 1-6.
- [21] Ezeobijesi, J., Bhanu., B., 2017. Latent fingerprint image segmentation using deep neural network. in Deep Learning for Biometrics. Springer. pp. 83-107.
- [22] Nguyen, D.L., Cao, K., Jain., A.K., 2018. Robust minutiae extractor: Integrating deep networks and fingerprint domain knowledge. in IEEE International Conference on Biometrics.
- [23] Khan, A.I., Wani, M.A., 2019. Patch-based Segmentation of Latent Fingerprint Images Using Convolutional Neural Network. in Appl. Artif. Intell. 33(1), 87-100.  
DOI: <https://doi.org/10.1080/08839514.2018.1526704>.
- [24] Fingerprint Minutiae from Latent and Matching Tenprint Images - NIST special database 27 (a); 2010.
- [25] Hornak, L., Ross, A., Crihalmeanu, S.G., et al., 2007. A protocol for multibiometric data acquisition storage and dissemination. tech. rep., West Virginia University.
- [26] Hicklin, A., 2007. Latent quality survey, Noblis .Org, Falls Church, VA, USA.
- [27] Karimi, A.S., Kuo, C.C.J., 2008. A robust technique for latent fingerprint image segmentation and enhancement. in Proceedings of the 15th IEEE International Conference on Image Processing. pp. 1492-1495.
- [28] Ezhilmaran, D., Adhiyaman, M., 2016. Edge Detection Method for Latent Fingerprint Images Using Intuitionistic Type-2 Fuzzy Entropy. Cybernetics and Information Technologies. 16(3), 205-218.
- [29] Yoon, S., Liu, E., Jain, A.K., 2012. On latent fingerprint image quality. In Proceedings of the International Workshop on Computational Forensics.
- [30] Feng, J., Zhou, J., Jain, A.K., 2013. Orientation field estimation for latent fingerprint enhancement. IEEE Transactions on Pattern Analysis and Machine Intelligence. 35(4), 925-940.
- [31] Li, J., Feng, J., Kuo, C.C.J., 2018. Deep-Convolutional Neural Network for latent fingerprint enhancement. Signal Process. Image Commun. 60, 52-63.
- [32] Joshi, I., Anand, A., Vatsa, M., et al., 2019. Latent Fingerprint Enhancement Using Generative Adversarial Networks. in {IEEE} Winter Conference on Applications of Computer Vision, {WACV}, Waikoloa Village, HI, USA. pp. 895-903.  
DOI: <https://doi.org/10.1109/WACV.2019.00100>.
- [33] Sankaran, A., Pandey, P., Vatsa, M., 2014. On latent fingerprint minutiae extraction using stacked denoising sparse autoencoders. In Proceedings of the International Joint Conference on Biometrics. pp. 1-7.
- [34] Paulino, A., Liu, E., Cao, K., et al., 2013. Latent fingerprint indexing: Fusion of Level- 1 and Level- 2 features. In Proceedings of the IEEE Sixth International Conference on Biometrics: Theory, Applications and Systems. pp. 1-8.
- [35] Su, C., Srihari, S., 2010. Latent fingerprint core point prediction based on Gaussian processes. In Proceedings of the 20th International Conference on Pattern Recognition. pp. 1634-1637.
- [36] Tang, Y., Gao, F., Feng, J., et al., 2017. FingerNet: An unified deep network for fingerprint minutiae extraction. in IEEE International Joint Conference on Biometrics (IJCB), Denver, CO, USA. pp. 108-116.  
DOI: <https://doi.org/10.1109/BTAS.2017.8272688>.
- [37] Darlow, L.N., Rosman, B., 2017. Fingerprint minutiae extraction using deep learning. in IEEE International Joint Conference on Biometrics, (IJCB), Denver, CO, USA. pp. 22-30.  
DOI: <https://doi.org/10.1109/BTAS.2017.8272678>.
- [38] Deshpande, U.U., Malemath, V.S., 2021. MINU-EXTRACTNET: Automatic Latent Fingerprint Feature Extraction System Using Deep Convolutional Neural Network. In Recent Trends in Image Processing and Pattern Recognition. RTIP2R 2020. Communications in Computer and Information Science, vol 1380. Springer, Singapore. pp. 44-56.  
DOI: [https://doi.org/10.1007/978-981-16-0507-9\\_5](https://doi.org/10.1007/978-981-16-0507-9_5).
- [39] Liu, E., Arora, S.S., Cao, K., et al., 2013. A feedback paradigm for latent fingerprint matching. In Proceedings of the IEEE International Conference on Biometrics. pp. 1-8.
- [40] Miguel Angel Medina-Pérez, Aythami Morales Moren., Miguel Ángel Ferrer Ballester, et al., 2016. Latent fingerprint identification using deformable minutiae clustering. Elsevier, Neurocomputing. 175, 851-865.
- [41] Deshpande, U.U., Malemath, V.S., Patil, S.M., et al., 2021. Latent fingerprint identification system based on local combination of minutiae feature points. Journal of SN Computer Science (SNCS), Springer, Article number - 206.  
DOI: <https://doi.org/10.1007/s42979-021-00615-7>.
- [42] Cao, K., Jain, A.K., 2018. Latent Fingerprint Recognition: Role of Texture Template. in 9th IEEE International Conference on Biometrics Theory, Applications and Systems, (BTAS), Redondo Beach, CA,



- USA. pp. 1-9.  
DOI: <https://doi.org/10.1109/BTAS.2018.8698555>.
- [43] Ezeobijesi, J., Bhanu, B., 2018. Patch Based Latent Fingerprint Matching Using Deep Learning. 25th IEEE International Conference on Image Processing (ICIP), Athens. pp. 2017-2021.  
DOI: <https://doi.org/10.1109/ICIP.2018.8451567>.
- [44] Nguyen, D.L., Jain, A.K., 2019. End-to-End Pore Extraction and Matching in Latent Fingerprints: Going Beyond Minutiae. CoRR, vol. abs/1905.11472. [Online] Available: <http://arxiv.org/abs/1905.11472>.
- [45] Deshpande, U.U., Malemath, V.S., Patil, S.M., et al., 2020. CNNAI: A Convolution Neural Network Based Latent Fingerprint Matching Using the Combination of Nearest Neighbor Arrangement Indexing. *Front. Robot. AI*, vol. 7.  
DOI: <https://doi.org/10.3389/frobt.2020.00113>.
- [46] Feng, J., Shi, Y., Zhou, J., 2012. Robust and efficient algorithms for separating latent overlapped fingerprints. *IEEE Transactions on Information Forensics and Security*. 7(5), 1498-1510.
- [47] Sankaran, A., Vatsa, M., Singh, R., 2015. Multisensor Optical and Latent Fingerprint Database. in *IEEE Access*. 3, 653-665.