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LATENT FINGERPRINT IMAGE ENHANCEMENT BASED ON OPTIMIZED BENT IDENTITY BASED CONVOLUTIONAL NEURAL NETWORK

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Abstract

Fingerprints are unique biometric systems (BSs) in which none of the human possesses similar fingerprint structures. It is one of the most significant biometric processes used in the identification of criminals. Latent fingerprints or latents are generated mainly by the finger sweat or oil deposits which is left by the suspects unintentionally. The impressions of latents are blurred or smudgy in nature and not viewed by naked eye. These fingerprints are of low quality, corrupted by noise, degraded by technological factors and exhibit minor details. Latents display consistent structural info when observed as an image. Image Enhancement is necessary in latents, to transform the latent (noisy) image into fine-quality (enhanced) image. In this work, a new image enhancement approach named BI-CNN (Bent Identity-Convolution Neural Network) with Spatial Pyramid Max Pooling (SPMP) model optimized using TSOA (Tunicate Swarm Optimization Algorithm) is presented to produce an enhanced latent at the output. This procedure involves the integration of ROI (Region Of Interest) Estimation, Anisotropic Gaussian Filter (AGF) based Pre-filtering, Fingerprint alignment using Sobel Filter, Intrinsic Feature patch extraction using Optimized BI-CNN, GAT (Graph Attention) network based Similarity Estimation followed by image reconstruction and feedback module. The implementation tool used in this work is PYTHON platform. The proposed optimized BI-CNN framework tested on dual public datasets namely IIITD-latent finger print and IIITD-MOLF have shown enhanced outcomes. Thus, the IIITD -latent fingerprint database obtained 83.33% on Rank-10 accuracy and 39.33% on Rank-25 accuracy.

Keywords: Latent Fingerprints, Image Enhancement, Convolutional Neural Network, Optimization Algorithm, Similarity Matching.

1. Introduction

Fingerprints have been globally recognized as the most important one in physical evidence of forensic science field [Singla *et al.* (2020)]. Forensic agencies routinely collect ten-print records of criminals caught using rolled and plain fingerprint formats [Deshpandeet *et al.* (2020)]. These formats are acquired professionally terms as reference fingerprints and have adequate ridge information for individual identification. Automated Fingerprint Identification System (In short, AFIS) which has been verified as most sophisticated method with the identification of high rank-1 ratio, particularly it designed for plain and rolled fingerprints [Gardner *et al.* (2017)]. Compared to reference fingerprints, latent fingerprints are imperceptible due to unintentionally deposited on objects present in the crime area. Typically, latent fingerprints are poor quality with the terms of ridge structure and high background noise which leads to unreliable feature extraction. Hence, identification of these fingerprints is more challenging one for forensic agencies in order to recognize the suspected persons who committed a crime [Chaidee *et al.* (2018)] and [Liban and Hilles (2018)].

To attain the order of high identification ratio for latent fingerprints, quality enhancement which basically needed for fingerprints before entering into the AFIS. The key goal of fingerprint enhancement is to generate another fingerprint in such a manner that, it exposes information for forensic examination more than the first fingerprint [Cao and Jain (2018)] and [Wang *et al.* (2018)]. The physical solution for fingerprint enhancement also possible through recapturing the fingerprint after certain time, this solution is typically impractical and time consuming. The enhancement of fingerprint can assist to upgrade the visibility of ridge structure, redeem corrupted region, eliminate background noise, and increase the contrast of ridge in some extent [Dabouei *et al.* (2018)] and [Zhang *et al.* (2018)]. These processes are not only related with image de-noising, restoration and up scaling, but also comprising the unique phase of latent fingerprints named as eliminating background noise. The reliability of feature extraction and further identification of higher ratio should be achieved after the enhancement of latent fingerprint identification [Ezeobiejesi and Bhanu (2018)] and [Deerada *et al.* (2019)].

In recent times, the nonlocal means (NLM) is recognized as a conventional algorithm which eradicates the background noise. Instead of individual pixels this method identifies the individual similarities between the image patches and every image pixel has restored with the help of search window based weighted average computation of all pixels [Liu *et al.* (2014)] and [Cao *et al.* (2014)]. Recently, the method of NLM has been extensively applied to remove the Gaussian noise in various fields. In spite of successfully removing Gaussian noise, the traditional NLM method is unsuitable for the reduction of speckle noise since the speckle noise is significantly different from Gaussian noise [Chaudhary *et al.* (2020)]. Basically, the most noise removal of NLM-based method which depends to consume the gray-level information and hand-crafted feature. In ultra sound mage, these features are not perfectly suited to represent the comparison of structural similarities between the image patches [Baig *et al.* (2015)]. For the computation of structural similarities, the intrinsic features which can be learned from the image of interest to obtain better enhancement of result. The popular algorithm of deep learning which contained by the research community of machine learning, the intrinsic features can automatically learn from the training data. Especially, the CNN is evidenced to be effective on both low-level as well as high-level applications in computer vision [Zou *et al.* (2013)] and [Sankaran *et al.* (2014)].

Motivation

Latent fingerprint matching is an emerging application in the field of forensic analysis to identify the person who involved in crime. The latent fingerprint regions can be corrupted due to the existence of background noise which results lack of quality and non-linear distortion in ridge details. In some instance, partial ridge details only available due to the unintentional deposition of fingerprints. Hence, noise removal and reconstruction of fingerprint image can be viewed as a pre-processing phase to simplify the process of Minutiae Point Extraction and fingerprint matching. In earlier literature, the latent fingerprint enhancement has been actively studied by various researchers based on conventional image filtering techniques such as median filter, non-local mean filter and wiener filter etc. The fingerprint orientation field (OF) estimation and reconstruction is significant one to enhance the fingerprint quality. The multi scale dictionary based techniques are well recognized for OF estimation with the aid of TV (Total Variation) and adaptive directional TV (ADTV) models. In recent times, deep learning model especially CNN has been well suitable for intrinsic feature extraction supported to computer vision tasks such as segmentation and enhancement. According to above discussed challenges, we have motivated to propose a deep learning (DL) based model with GAT Network model for latent fingerprint enhancement.

Research Objectives

The major objective of this paper is to develop a CNN based DL model which exploits the intrinsic features involved in latent fingerprint image and utilizes the structural similarity between input and feature image patch to perfectly remove background noise for enhancement and retain ridge details for fingerprint matching. The key contributions to this work are précised as follows:

- A new BI-CNN based intrinsic FE (Feature Extraction) is introduced to directly learn the intrinsic features involved in latent fingerprint image, which contributes to precisely remove the background noise for fingerprint enhancement.
- Swarm Algorithm named TSOA is used to tune the BI-CNN hyper-parameters. It also helps to avoid the DL model producing irregular feature vector and remove the background noise more accurately with minimal computation time.
- Utilize the SPMP layer to regularize the output of the last convolutional layer. This layer aggregates the features of the last convolution layer through spatial pooling, where the size of the pooling regions is dependent on the size of the input.
- Image enhancement using optimized BI-CNN improves the overall performance and extracts the important details from latent fingerprints. The final, feedback module is enhance the LR (Low Resolution) image into HR (High Resolution) images that signifies the enhanced output image which signifies improved clarity in ridge as well as valley structure.

The organization of this work is systematized as: Section 2 defines the recent related works. The proposed method is explained clearly in Section 3. Implementation outcomes are illustrated in Section 4. The conclusion about this work is stated in Section 5 with future suggestion.

2. Related Works

Some of the current research works interrelated with the Latent fingerprint enhancement are listed below:

2.1 Latent Pre-processing

Cao [Cao and Jain (2018)] presented ConvNets (Convolutional Neural Networks) based automatic recognition of latent fingerprints. The cropping procedure called ROI was done, as the latent image include multiple fingerprints of same or different person. The major challenges being faced in latent images were low contrast FR (Friction Ridge) structure, background noise and smaller FR area. ROI was outlined and marked in red color to effectively highlight the FR region.

Ezeobiejesiet [Ezeobiejesi and Bhanu (2017)] introduced a deep learning framework called DANN (Deep Artificial Neural Network) for latent image segmentation. Initially, the latents were partitioned into non-overlapping blocks to represent both the fingerprint and non-fingerprint regions. DANN executes learning and classification in which the unsupervised pre-training (first phase) includes identity mapping (learning) of the input image patches. Next, fine-tuning (second phase) was done for cost function minimization.

Choi *et al.* [Choi *et al.* (2012)] discussed the segmentation procedure for latent fingerprints in an automated manner by means of orientation tensor method. This approach was utilized to remove the structural noise in background and extract fingerprint symmetric patterns. A local FA (Fourier analysis) technique was used for local frequency estimate in latent image and effective frequency ranges were considered for locating fingerprint regions. The foreground (candidate fingerprint) regions was obtained for each feature such as frequency, orientation also localized the regions of latent fingerprint using the connection of candidate regions.

Zhang *et al.* [Zhang *et al.* (2013)] offered an adaptive TV (total variation) model for segmentation of latent fingerprints. This model was made adaptive by altering the fidelity coefficient L_1 which divides the textures of foreground with background. The fidelity model was used to remove the background noise in latent fingerprint images. The proposed method was tested on the 3 sample images from the latent database NIST SD-27. However, these algorithms have the limitation that it gives poor performance on latents with low quality.

2.2 Latent Feature Extraction

The latent fingerprint quality enhancement is presented by researchers [Manickam *et al.* (2019)] with the aid of intuition type-2 fuzzy set. Moreover, Scale Invariant Feature Transformation (SIFT) and minutiae points was employed to matching the latent fingerprints. Initially pre-processing was carried out by the help of Binarization and Thinning to upgrade and convert the grayscale image into binary image. In order to achieve enhancement, for further processing method the original image was divided into six windows and every window that has been maintained at the same size. Finally, simulation results were showed that minutiae points achieved high matching scores compared to SIFT points for both FVC-2004 and IIIT-latent fingerprint databases.

Tang *et al.* [Tang *et al.* (2017)] discussed about FCN (Fully Convolutional Network) for extracting minutiae in latent fingerprints. As latent images are of poor quality, it was very difficult to extract consistent minutiae. Using FCN, the minutiae proposals were generated from raw (original) latent image directly with the minutia-score map. Minutiae include bifurcation and ridge ending. Finally, CNN was learned to classify the pixel proposals and compute minutiae orientations.

Sankaran *et al.* [Sankaran *et al.* (2014)] presented the extraction of minutiae feature in latents using SAE (Stacked Auto Encoder). Automatic latent image detection performance was limited because of the inaccurate minutiae (feature) extraction[Cao and Jain (2018)]. Using the de-noising sparse SAE model, the dual descriptors such as minutia, non-minutia can be learned from the tenprint latent patches. Minutia extraction in latents can be modelled as a binary classification problem as the latents possess high noise structures and it was imperative to learn de-noised feature descriptor for minutiae.

2.3 Latent Fingerprint Image Enhancement Techniques

The integration of Generative Adversarial Network (GAN) for latent fingerprint quality enhancement was discussed by researchers [Joshi *et al.* (2019)] to upgrade the low quality ridges and predict the ridge information. The proposed algorithm comprising two networks: a latent enhancer network and an enhanced fingerprint discriminator network. The former network was responsible for upgrading the quality of given latent fingerprint whereas the second network was used to categorize the query of input image whether it was real enhanced image that were produced by Latent enhancer network. Simulations has been conducted with two available public dataset, IIITD-MOLF and IIITDMSLFD and results revealed to proposed the GAN model significantly improve the matching accuracy 35.66% for enhanced latent images and raw images achieved 12.59% matching accuracy.

The advanced enhancement technique for latent fingerprints was presented by Srisutheenon *et al.* [Srisutheenon *et al.* (2019)] based on semi-automatic manner. This technique involved three inputs such as manual segmentation, latent fingerprint image, and location of initial block. The presented technique begins upgrading the initial block by matched filter. Further the upgraded block was padded posterior to input latent image. The presented technique executes iterative enhancement with feedback until the entire segmentation was filled using enhanced blocks. Simulation has been carried out on public database NIST SD27 and results prove that the presented technique beats other methods with the performance identification accuracy (IA).

Li *et al.* [Li *et al.* (2018)] have presented the enhancement method called FingerNet that has motivated through the recent growth of CNN. The FingerNet had three major parts such as one convolution part which were shared using dual de-convolution parts. The fingerprint features were extracted with the first Therefore, the development of de-convolution branch was employed to eliminate the structured noise as well as enhance fingerprints. Orientation of de-convolution branch could perform the guiding enhancement task which was formulated using the strategy known as multi-task learning. So, the trained network with end-to-end learning combined with pixel-to-pixel manner could able to directly boost the output of latent fingerprint.

Qian *et al.* [Qian *et al.* (2019)] had designed the method of latent fingerprint enhancement using Dense UNet. Initially, the training data could generate fingerprints with higher-quality and those fingerprints were overlapped due to the presence of structured noises. Next, using the deep DenseUNet, fingerprint image could transform from the image with low-quality into high-quality latents through end- to-end training. Lastly, the enhancement of whole latent fingerprint would achieve the requirement of image quality with DenseUNet model. The simulation has been conducted on latent fingerprint NIST SD27 database and results showed that the designed model achieved 58.2% matching accuracy and only 0.7 seconds required for computation.

As latent fingerprint images are subject to low quality with uncertainties in ridge structures, it is necessary to improve the quality of original image. Different fingerprint features such as ridge orientation map, singular points, pores, incipient ridges, frequency map and dots, consumes much time for extraction. However, when analyzing the improved fingerprint images, challenges such as spurious features are generated when the latent image contain inadequate ridge information. Hence, the proposed BI-CNN optimized with TSOA and the adopted SPMP layers combined with GAT similarity matching and feedback module offers enhanced latent fingerprint image structures more accurately.

3. Proposed Methodology

The process of Latent fingerprint identification is imperatively required for law enforcement and forensic agencies to identify the suspected persons involved in crime. Nevertheless, automatic matching of latent fingerprints with a gallery of reference fingerprints is considered more challenging because of the certain complicated elements such as low clarity ridge structure, overlapping unstructured noise and noisy background.

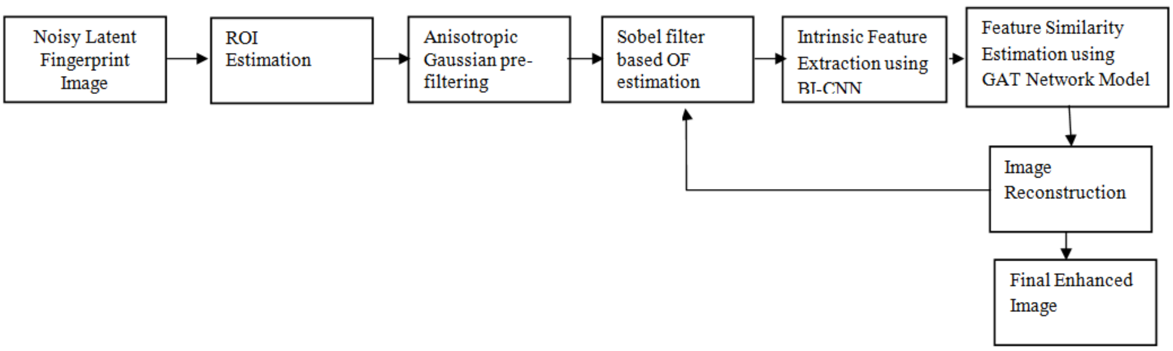


Fig 1: Proposed Process Flow Model

In order to successfully match the latent fingerprints, an innovative Latent fingerprint enhancement model is required to achieve reliable minutiae extraction. In this paper, an optimized BI-CNN with SPMP model is proposed for intrinsic feature extraction. The hyper parameters tuning process of BI-CNN is achieved by TSOA. Further, each intrinsic feature patch is fed into the GAT for similarity estimation. Next, image reconstruction is to enhance the low clarity ridges and predict the ridge information accurately. Finally, the feedback module is employed to enhance the low resolution image into high resolution images. The process flow of proposed model is shown in Fig 1. The processes involved in latent fingerprint image enhancement model are: ROI Estimation, Pre-filtering, Fingerprint alignment, Intrinsic Feature extraction, Similarity Estimation, Image Reconstruction and Feedback Module.

Initially, the ROI estimation is done in the original noisy fingerprint image. ROI involves separating the foreground latent fingerprint from its background. Next, only the foreground latent fingerprint region is chosen which is pre-filtered by the help of AGF. Further, the pre-filtered image is inputted to the Sobel filter, employed with the purpose of orientation field (OF) estimation for fingerprint alignment. After orientation correction, patched based feature extraction process is employed by BI-CNN to generate the intrinsic feature vector of image patch. Adopt spatial pyramid max pooling layer to regularize the output (intrinsic feature image) of the last convolutional layer. Tuning the hyper parameters of BI-CNN using an algorithm called TSOA for precise feature extraction. Compute the similarity feature images using GAT model. Based on the computed similarity the input image is reconstructed for enhancement. Further, any enhancement is needed for input image, the feedback module is adopted to re-activate the BI-CNN and GAT model.

3.1 ROI Estimation:

Latent fingerprints are formed from the traces of oil, sweat and other natural skin secretions present on the fingers of criminal's. Usually, the latent fingerprints are gathered from the crime scene which indicates the finger impression of a criminal. These fingerprints can be mixed with objects, other fingerprints and structured noise. Initially, the ROI estimation is done in the original noisy fingerprint image. ROI involves separating the foreground latent fingerprint from its background. ROI accurately labels all the foreground regions, while including as minute background information as possible. ROI separates the original image into fingerprint region and non-fingerprint region.

3.2 Noise Removal using AGF

The latent fingerprint processing is subject to the difficulties like presence of various structured background noise and fingerprint patterns with poor quality. In this step, only the foreground latent fingerprint region is chosen which is pre-filtered by the help of AGF [Khan *et al.* (2017)]. A latent fingerprint often represents very low quality with blurred or smudged ridges. The different types of structured noise in latent fingerprints are named as arch, character, line, stain, speckle and others. Fig 2 signifies the representation of noisy latent fingerprints.

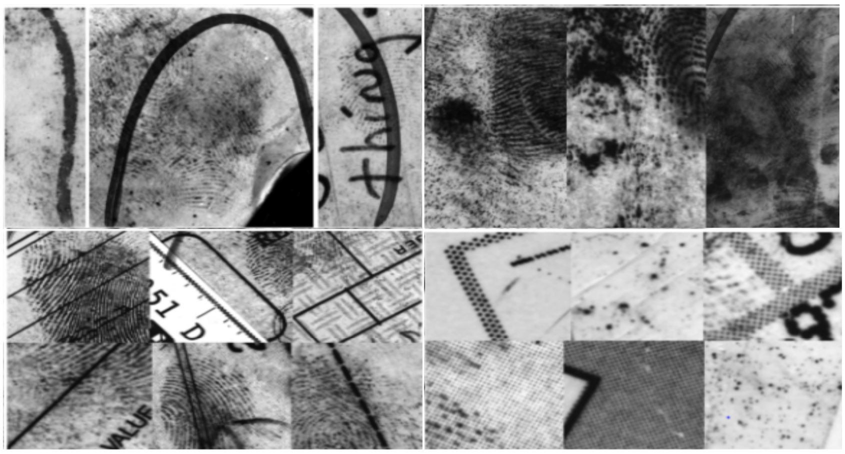


Fig 2: Noisy Latent Fingerprints [Zhang *et al.* (2013)]

Arch is termed as the simplest noise type in which the presence of latent fingerprints in a particular region are marked or encircled. Character noise can be typed or handwritten. It can seem with numerous font sizes, types etc. Line noise can occur in the form of multiple lines or a single line. Stain noise occurs if the fingerprint is created on dirt or wet surface. Speckle noise signifies tiny-scale structures which are random (dust, ink) or regular (clusters of minor points). The other noise types are signs, arrows etc. The noise present in the latent fingerprints denotes the random error in pixel values. In order to remove the noise, a pre-filtering technique named AGF is used. The main function of AGF is ridge structure enhancement and noise elimination. The kernel function is expressed as,

$$GF(m,n;\theta,k,\sigma_m,\sigma_n)=e^{-\left(\frac{m_\theta^2}{2\sigma_m^2}+\frac{n_\theta^2}{2\sigma_n^2}\right)} \quad (1)$$

The representation of GF (Gaussian Filter) is separated into two filters namely isotropic and anisotropic filter for simpler implementation process. As, $\sigma_n^2 << \sigma_m^2$ then the filter is separated into isotropic and anisotropic filter given by,

$$GF_{iso}(n;\sigma_n)=e^{-\frac{m^2+n^2}{2\sigma_n^2}} \quad (2)$$

$$GF_{aniso}\left(m_{\theta};\theta,\sigma_{\theta}\right)=e^{-\frac{m_{\theta}^{2}}{2\sigma_{\theta}^{2}}} \tag{3}$$

where, $\sigma_{\theta}^{2}=\sigma_{m}^{2}-\sigma_{n}^{2}\approx\sigma_{m}^{2}$ and $x_{\theta}=m\cos\theta+n\sin\theta$. Here, the oriented GF is implemented by convolution with 2D (2 Dimensional) isotropic GF having size equivalent to σ_{n} . Then the resultant image is being convolved with 1D (1 Dimensional) gaussian at direction θ. By varying the value of $\theta$from pixel to pixel the AGF can obtain a smoothed image. This filter can improve the image quality and suppress the vertical or horizontal image features. One of the major characteristics of AGF is, it permits quick evaluation of ridge structures with high angular and spatial accuracy. Hence, this pre-filtering process can remove the noisy features and highlight only the wanted features.

3.3 Fingerprint Alignment-Sobel filter based OF estimation

In fingerprint pre-processing, estimating the OF is an important step. Here, Sobel filter is employed for OF estimation. The term orientation gives the direction of fingerprint gradient. OF estimation is executed block wise $(W\times W)$ [Kekre and Bharadi (2009)]. Gradient represents the variation of grey level gradually. The direction of gradient is mentioned by means of arrows. The ridge structure is perpendicular to the gradient. To estimate the orientation of fingerprint, it should be separated into $(W\times W)$blocks. For every block, the GA (gradient angle) θ is estimated which is further called as OF angle. Here, the gradient operator (GO) named 3×3Sobel operator is used. In a selected block, the ridge structure consists of dual edges and the gradient vectors are opposite to each other. In order to calculate the dominant gradient angle $\overline{\varphi}$, the average of gradient angle is taken directly in a local base block and the opposite gradients at both sides may cancel each other. To solve this issue, the gradient angles are doubled before the averaging procedure which is expressed as 2φ. The angles of the squared gradient vectors $[G_{sm},G_{sn}]^{T}$ is 2φ which is related with $[G_{m},G_{n}]^{T}$ based on the trigonometric identities,

$$\begin{pmatrix}G_{sm}\\G_{sn}\end{pmatrix}=\begin{pmatrix}G^{2}\cos2\varphi\\G^{2}\sin2\varphi\end{pmatrix}=\begin{pmatrix}G_{m}^{2}\\2G_{m}G_{n}\end{pmatrix} \tag{4}$$

The expression to calculate the average squared gradients $\left[\overline{G_{sm}},\overline{G_{sn}}\right]$ with block size $(W\times W)$ is represented as:

$$\begin{pmatrix}\overline{G_{sm}}\\\overline{G_{sn}}\end{pmatrix}=\begin{pmatrix}\sum_{W}G_{sm}\\\sum_{W}G_{sn}\end{pmatrix}=\begin{pmatrix}\sum_{W}\left(G_{m}^{2}-G_{n}^{2}\right)\\\sum_{W}2G_{m}G_{n}\end{pmatrix} \tag{5}$$

The input fingerprint image is divided into $(W\times W)$pixels. The expression to calculate the OF direction is:

$$\theta_{OF}=\frac{1}{2}\tan^{-1}\left(\frac{\sum_{i=1}^{W}\sum_{i=1}^{W}2G_{m}(i,j)G_{n}(i,j)}{\sum_{i=1}^{W}\sum_{i=1}^{W}\left(G_{m}^{2}(i,j)G_{n}^{2}(i,j)\right)}\right)+\frac{\pi}{2} \tag{6}$$

where, θ_{OF} specifies the OF direction whereas the range varies in-between $[0,\pi]$. The equation (6) is perpendicular to the direction of gradient and provides the ridge direction. To estimate the reliability, another parameter named coherence is evaluated which signifies the averaged gradients strength.

$$C_{W}=\frac{\left|\sum_{i=1}^{W}\sum_{i=1}^{W}\left(G_{sm}(i,j)G_{sn}(i,j)\right)\right|}{\sum_{i=1}^{W}\sum_{i=1}^{W}\left|G_{sm}(i,j)G_{sn}(i,j)\right|} \tag{7}$$

where, C_{W} indicates the coherence measure.

3.4 Intrinsic Feature Extraction- Optimized BI-CNN

The process of minimizing the total number of features in a dataset and creating a new set of reduced features is termed as feature extraction. In this work, the intrinsic feature extraction using BI-CNN [Fan *et al.* (2020)] aims at differentiating the objects shading and reflectance from a single image. Some of the advantages of intrinsic feature extraction are: minimizes the over fitting risks, improvements in accuracy and speedup the training process. In this work, BI-CNN act as a FCN (Full Convolutional Network) model. The architecture of BI-CNN is shown in Fig 3.

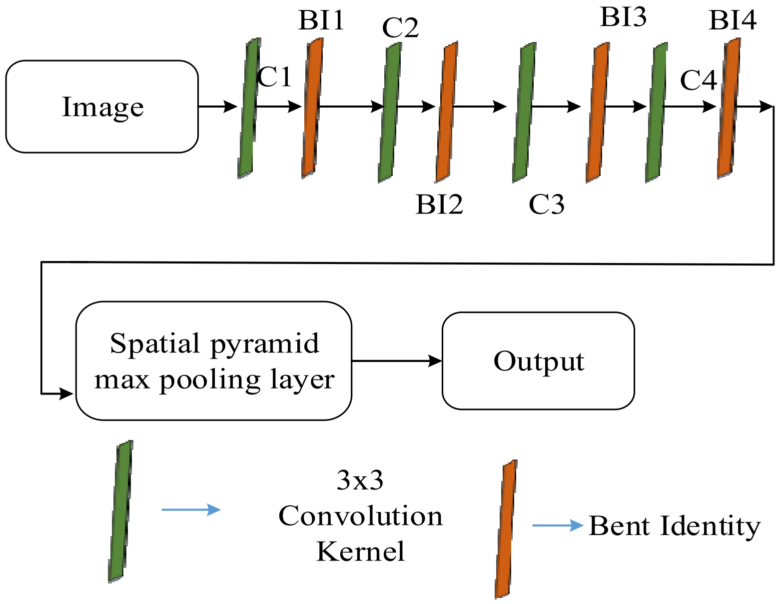


Fig 3: Architecture of BI-CNN

The term Bent Identity (BI) is chosen as activation function, as it includes output mean nearby zero and soft saturation that can improve the robustness of the model. The output features of 1st convolution layer (C_1) is combined with BI function and connected to next convolution layer (C_2). In BI-CNN, the last convolution layer (CL) is not connected with the bent activation and use a filter of size (3×3). While the rest of the CLs use (3×3) sized 64 filters each being connected with the activation layer. In order to make sure that the size of the input and output image are similar, zero padding operation is performed in advance of each CL. BI-CNN aims to extract the diverse feature info present in the image completely and transform that info to the output end. In BI-CNN, the noise in an image is assumed as $Y = X + n$, where Y, X signifies the noisy, clean image and n denotes the Gaussian noise of σ (standard deviation). To minimize the difference among clear and ideal image, the loss function can be expressed as,

$$L(W,b) = \underset{W,b}{\operatorname{argmin}} \frac{1}{2N}\sum_{i=1}^{N}\left\| X_i - \hat{X}_i \right\|^2 \tag{8}$$

where, the weight matrix is denoted as W, the bias is b, the noise image Y, ideal clean image X and $\hat{X}_i$ indicates the estimated clean image. The BI is chosen as activation function is given as,

$$f(x) = \frac{\sqrt{x^2+1}-1}{2} + x \tag{9}$$

The mathematical expression for the (C_1) output is represented as:

$$C_1 = \sum_{ic=1}^{64} W_{3\times 3}^{1} \times Z + b^1 \tag{10}$$

where, $W_{3\times 3}^{1}$ indicates the size of (C_1), whereas the lower term is size of filter and upper term is the layer, Z signifies the noisy image patches and the number of input channels is denoted as ic.

$$C_2 = BI(C_1) = \begin{cases} C_1, \sum_{j=1}^{n} W_j Z_j > 0 \\ \delta\left(e^{C_1} - 1\right), \sum_{j=1}^{n} W_j Z_j \le 0 \end{cases} \tag{11}$$

where, the activation function is represented as $BI(\ )$. The weight value is denoted as W_j and the image pixel is represented as Z_j. The hyper-parameter notation is $\delta > 0$.

$$C_2 = \sum_{ic=1}^{64} W_{3\times 3}^{2} \times C_{1_{BI}} + b^2 \tag{12}$$

$$C_3 = \sum_{ic=1}^{128} W_{3\times 3}^{3} \times C_2 + b^3 \tag{13}$$

$$C_4 = \sum_{ic=1}^{128} W_{3\times 3}^{4} \times C_3 + b^4 \tag{14}$$

In this BI-CNN model, a new pooling strategy is adopted by replacing the last CL (C_5) in BI-CNN architecture which is named as SPMP layer. It involves the combination of dual layers such as SP (Spatial Pyramid) and MP (Max Pooling). The main functionality of SPMP layer is, it creates fixed-length illustrations in image scale/size and enhance the feature extraction process. With this adopted layer, the input image with variable sizes can be resized to any different scales. Also, the feature maps are evaluated from the whole image only once and evade the computation of convolutional features repetitively. Equation (11) represents the hyper-parameter notation. In order to tune the hyper-parameters, an optimization algorithm named TSOA is used.

TSOA is a meta-heuristic bio-inspired algorithm that imitates the swarm behaviour and jet propulsion of tunicate swarms at the time of navigation and hunting. Tunicate is a type of marine animal which is smaller in size and live in groups. Tunicates are attached to rocks, bottom of boats or docks. The sizes of this animal are of few mm (millimeters) and have the ability to produce a light of pale blue-green colour. Each tunicate is capable of collecting water from sea and produces a jet propulsion which helps them to traverse in the ocean vertically. This is the only animal in the ocean that migrates with fluid based jet propulsion. The most fascinating behaviour of tunicate animal is the swarm behaviour and jet propulsion nature. The mathematical modeling involves the following steps: Conflicts avoiding, Movement towards best neighbour, Converge and Swarm behaviour. Let the population of tunicate is denoted as $\overrightarrow{TU_{pop}}$, choose the maximum number of iterations Max_{iter} and initial parameters. In conflicts avoiding phase, the conflicts among search agents is avoided. Here, the $\overrightarrow{SA}$ (vector) is used to evaluate the position of new search agent which is expressed as,

$$\overrightarrow{SA} = \frac{\overrightarrow{GF}}{\overrightarrow{S}} \tag{15}$$

$$\overrightarrow{GF} = s_2 + s_3 - \overrightarrow{WF} \tag{16}$$

$$\overrightarrow{WF} = 2 \cdot s_1 \tag{17}$$

where, the random numbers are denoted as s_1, s_2, s_3 that ranges from [0, 1], $\overrightarrow{WF}$ signifies the advection of water flow, $\overrightarrow{GF}$ illustrates the gravity force and $\overrightarrow{S}$ denotes the social forces among search agents. The expression for $\overrightarrow{S}$ is,

$$\overrightarrow{S} = \lfloor L_{\min} + s_1 \cdot L_{\max} - L_{\min} \rfloor \tag{18}$$

where, $L_{\min}$ indicate the initial speed with value 1 and $L_{\max}$ denote the subordinate speed with value equal to 4. In the movement phase, the search agents move towards the best neighbour direction.

$$\overrightarrow{D} = \left| \overrightarrow{F_p} - rn \cdot \overrightarrow{TU_{pop}}(x) \right| \tag{19}$$

where, the distance among the food and search agent is represented as $\overrightarrow{D}$, present iteration is mentioned as x, the position of food is denoted as $\overrightarrow{F_p}$ and rn signifies the random number in range [0,1]. In converge phase, the search agent converge towards the food source (best search agent).

$$\overrightarrow{TU_{pop}}(x) = \begin{cases} \overrightarrow{F_P} + \overrightarrow{SA} \cdot \overrightarrow{D}, if\ rn \geq 0.5 \\ \overrightarrow{F_P} - \overrightarrow{SA} \cdot \overrightarrow{D}, if\ rn < 0.5 \end{cases} \tag{20}$$

However, in tunicate swarm behaviour phase, the first dual optimal best solutions gets saved and other search agents positions are updated based on the best search agent position.

$$TU_{pop}(\vec{x}+1) = \frac{\overrightarrow{TU_{pop}}(x) + TU_{pop}(\vec{x}+1)}{2+s_1} \quad (21)$$

In BI-CNN, equation (21) is used to tune the hyper-parameters. After the tuning process, the features are extracted in a precise manner. Table 1 illustrates the proposed (Optimized BI-CNN) model parameters.

Layer (Type)	Kernel size	Output shape	Parameters	Activation Function	Padding
Input (Input Layer)	-	80*80*3	0	-	-
Con_2D_1(con2D)	64	[(None,80, 80, 64)]	1792	BI	0
Con_2D_2(con2D)	64	[(None,80, 80, 64)]	36928	BI	0
Con_2D_3(con2D)	128	[(None,80, 80, 128)]	73856	BI	0
Con_2D_4(con2D)	128	[(None,80, 80, 128)]	147584	BI	0
Total parameters:555,328 Trainable parameters:555,328 Non-trainable parameters: 0					

Table 1. Optimized BI-CNN model parameters

3.5 Similarity Estimation

Further, each intrinsic feature patch extracted is fed into the GAT layers for similarity estimation. This estimation process can enhance the low clarity ridges and predict the ridge information accurately. For the matching process, GAT uses a pair of graphs as input and calculates the similarity score between the graph pairs. GAT based similarity estimation aims to exploit the similarity among diverse images in the LR (Low Resolution) feature space. Then, the identical pairs of images are matched and further the GAT mechanism (Graph networks) work as a strategy of self-similarity that allocates higher scores to identical features and more significant features. However, the output obtained from the intrinsic feature extraction is LR features having dimensions equivalent to $h \times w \times d$, where *d* signifies the feature channels number, $h$and w illustrates the spatial dimension. These features are given to the GAT network.

The similarity estimation using GAT, helps to get better image structure. In GAT, the LR features are reshaped to a size of matrix $n \times d$, $n = h/s \times w/s$. Also, the set of node features are updated using GAT and forms new feature set represented as,

$$h'''' = \left\{\vec{h}_1'', \vec{h}_2'', \vec{h}_3'', \ldots, \vec{h}_M''\right\}, h_a'' \in \Re^{NF} \quad (22)$$

where, the number of nodes is signified as M, and the features number is denoted as NF. Next, the LL (Learnable Linear) transformation function is expressed as,

$$g_{ab} = \alpha\left(We\vec{h}_a, We\vec{h}_b\right) \quad (23)$$

where α represents the attention coefficient. In order to, normalize the attention coefficient the softmax function is used.

$$\alpha_{ab} = soft\max(g_{ab}) = \frac{\exp(g_{ab})}{\sum_{l \in M}} \exp(g_{ab}) \quad (24)$$

Next, a weight matrix $\vec{\alpha} \in \Re^{2NF'}$ is used to optimize the self-attention coefficient α . Then, the non-linearity function called LReLU (Leaky Rectified Linear Unit) is applied with the self-attention equation (25).

$$\alpha_{ab} = \frac{\exp\left(L\mathrm{Re}LU\left(\vec{\alpha}^{Tr}\left[We\vec{h}_a \| We\vec{h}_b\right]\right)\right)}{\sum_{l \in M_a} \exp\left(L\mathrm{Re}LU\left(\vec{\alpha}^{Tr}\left[We\vec{h}_a \| We\vec{h}_b\right]\right)\right)} \quad (25)$$

$$\vec{h}_a'' = \sigma\left(\sum_{b \in M} \alpha_{ab} We\vec{h}_b\right) \quad (26)$$

where, $\|$ represents the concatenation and $(\cdot)^{Tr}$ signifies the transpose operation. Hence the similar features are obtained from output equation (26).

3.6 Image Reconstruction and Feedback Module

Image reconstruction is done to eliminate the image artifacts. The term artifact refers to any of the feature in the image which is different from the original image. Using image reconstruction, the low clarity ridges are enhanced and the ridge information is predicted accurately. Finally, the feedback module is employed to enhance the LR image into HR (High Resolution) images that signifies the enhanced output image.

4. Simulation Result

This section describes about the details of implementation tool, dataset used and performance analysis using the measures MSE, PSNR, RMSE. The research on latent fingerprint image enhancement is performed on the database called IIITD latent fingerprint and IIITD MOLF database. IIITD latent fingerprint is a publicly available dataset which includes only the impressions of latent images obtained from 15 subjects of every10 fingers. This database includes the images captured from multiple illustrations which enables the comparison between the latent-to-latent fingerprints (L2L) matching. Also, IIITD MOLF is a public source systematized in 6 folders such asDB1, DB2, DB3, DB3_A, DB4, and DB5 that enables the comparison between the latent-to-sensor (L2S) matching.

4.1 Implementation Tool Details

In this work, the latent fingerprint image enhancement is implemented using PYTHON tool-Anaconda navigator spyder 3.6 IDE. This is a TensorFlow based open source platform.

4.2 Description about Dataset

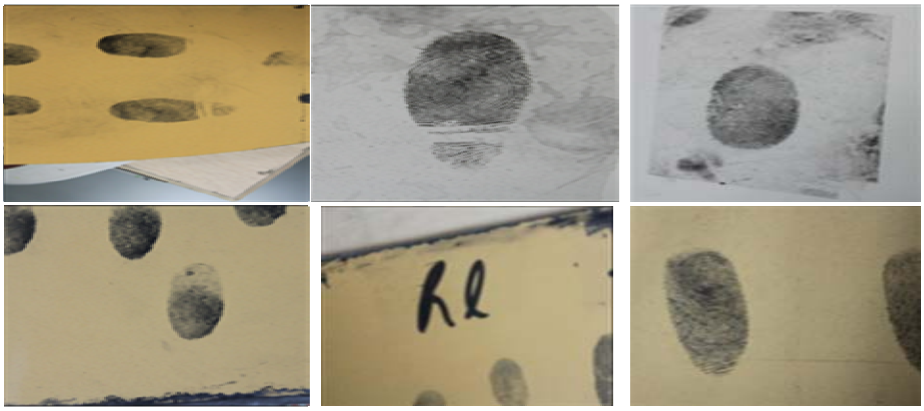


Fig 4: Sample images from IIITD- latent fingerprint database(http://iab-rubric.org/resources.html)

Sample images from IIITD-latent database are shown in Fig 4. The dataset used for experimentation is named as IIITD (Indraprastha Institute of Information Technology, Delhi) –latent fingerprint. This dataset includes total 1235latent fingerprints, of these 1040 images represent latent images from IIITD_Latent_Database, 45 latent images are of 500ppi (pixels per inch) obtained from IIITD_Latent_Mated_500ppi and 150latent images are of 1000 ppi obtained from IIITD_Latent_Mated_1000 ppi. From dual different backgrounds such as card, tile these latent images are lifted. Moreover, these fingerprints are captured using the camera-Canon EOS 500D at 4752× 3168 resolution.

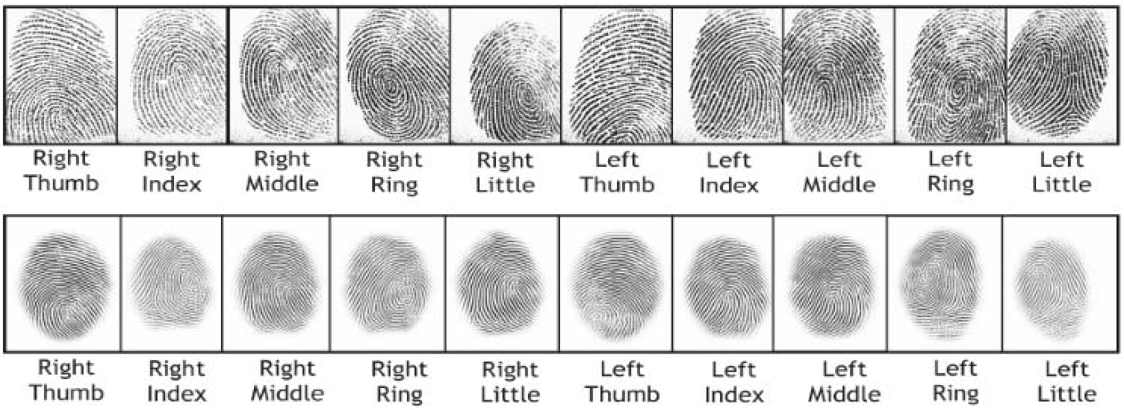


Fig 5: Sample images from IIITD- MOLF database (http://iab-rubric.org/resources/molf.html)

Fig 5 illustrates the sample images from IIITD-MOLF database. This dataset involves total 19,200 images of fingerprints being gathered from 100 individuals (subjects) via 5 different capturing procedures like Secugen Hamster-IV, Lumidigm Venus IP65 Shell, Latent fingerprints, Cross Match L-Scan Patrol and simultaneous latent fingerprints (Black powder dusting process).The DB1 subset includes 4000 images with size 352×544 captured using Lumidigm Venus. The DB2 subset contains 4000 images with size 258×336 captured using Secugen Hamster-IV. The subset DB3 involves 12000 images with size 1600×1500 captured using CrossMatch L-Scan Patrol. The subset DB3_A specifies the cropped prints from DB3 which holds 4000 images of variable size. The subset DB4 holds 44000 with variable size captured using latent fingerprints, cropped from simultaneous prints. The DB5 subset consists of 1600 images with annotated ROI simultaneous impression, minutiae and core points of size 1924×1232 .

4.3 Performance Analysis

The metrics namely MSE, PSNR and RMSE are used to measure the performance of the proposed Optimized BI-CNN method.

- MSE (Mean Square Error):This is an error metric used to measure the difference between the original and enhanced images. The formula to represent MSE is stated as:

$$MSE = \frac{1}{PQ}\sum_{i=0}^{P-1}\sum_{j=0}^{Q-1}\left\|\left(I_i(i,j) - I_e(i,j)\right)^2\right\| \tag{27}$$

  where, P and Q represent the number of rows and columns of image pixels.

- PSNR(Peak Signal to Noise Ratio): This metric is used to find the similarity among the enhanced and the original image. The formula to represent PSNR is stated as:

$$PSNR = 20\log_{10}\left(\frac{Max_f}{\sqrt{MSE}}\right) \tag{28}$$

  where, the maximum value of original image is indicated as Max_f .
- RMSE (Root Mean Square Error):This metric is named as a quadratic scoring (QS) which computes the average magnitude of error. It is defined as the squared difference among actual and predicted values.

$$RMSE = \sqrt{\frac{1}{PQ}\sum_{i=1}^{P}\sum_{j=1}^{Q}\left(I_i(i,j) - I_e(i,j)\right)^2} \tag{29}$$

- Matching: For the matching process, dual publicly existing feature extractors (ABR11, MINDTCT) and a matcher (MCC) has been employed.
- Ranking Accuracy: This is a commonly used metric in the literatures of computer vision to evaluate the accurateness of the presented system. Rank-25, 50 accuracy metrics are mostly used. It's an extension to Rank-1 Accuracy where instead of checking if the most probable class label equals to the true label, we check if the true label is in the top 25, 50 most probable labels.

With the above measures, the performance of the proposed method (Optimized BI-DNN) in enhancing the latent fingerprint image is verified.

Metrics/Database	MSE	RMSE	PSNR
IIITD-Latent Fingerprints	0.56225	0.7498	82.3904
IIITD-MOLF	0.572	0.7563	83.14

Table 2: Performance of Optimized BI-CNN

Table 2 illustrates the enhanced performance using Optimized BI-CNN. The proposed model (Optimized BI-CNN) based latent fingerprint image enhancement is evaluated by means of the measures such as MSE, PSNR and RMSE. The results acquired by evaluating the two datasets are mentioned in terms of MSE, PSNR and RMSE. The metrics MSE and RMSE are the error measures. PSNR measures the quality among the original and the enhanced image. Here, using this metric the image quality is assessed in which higher PSNR signifies better image quality.

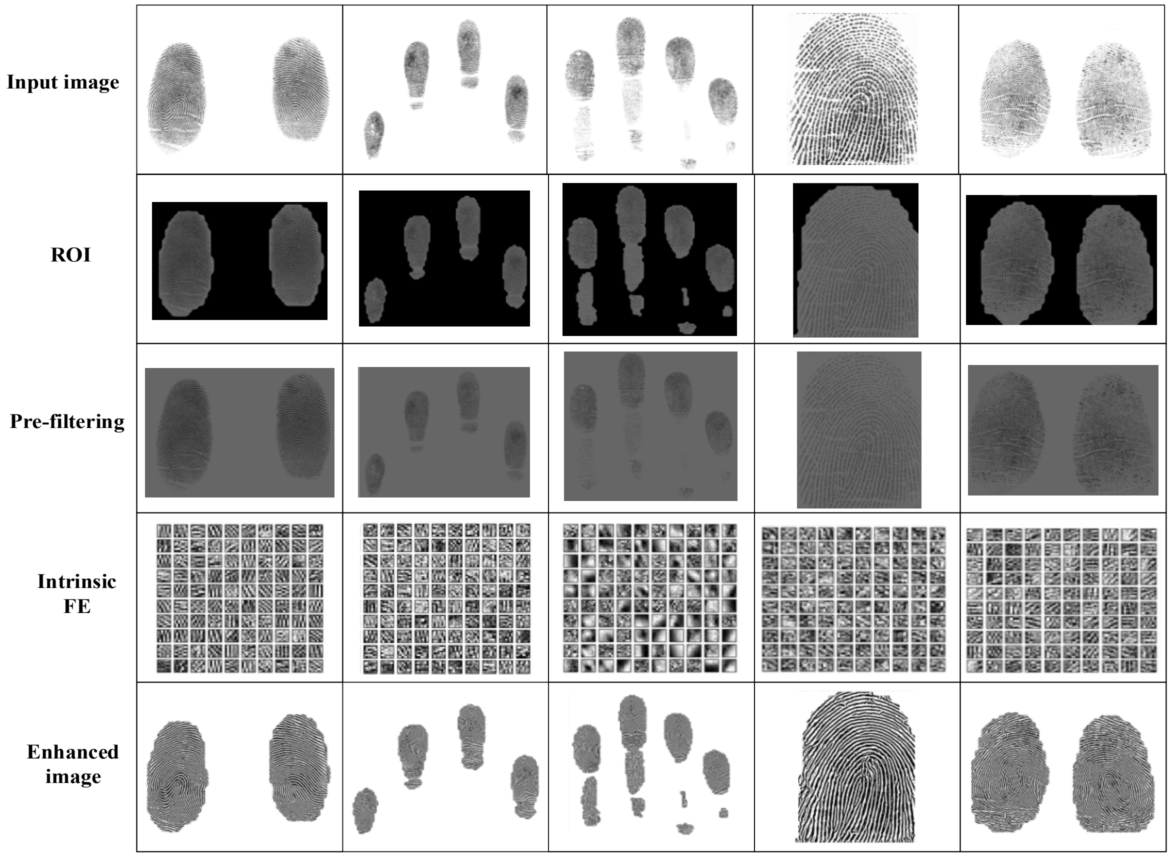


Fig 6: Experimental Outcomes on Image Enhancement (IIITD – latent fingerprint)

Fig. 6 specifies the experimental outcomes on image enhancement acquired from IIITD-latent fingerprint database. Here, 5 sample images are chosen from the database which is illustrated with its enhanced image structure. Also, the outcome based on step-by-step procedure is explained using image structures. Enhanced image structures helps in recognizing the image quality improvement. Optimized BI-CNN based latent fingerprint image enhancement refines the original image in which the desired features of latent fingerprints are easily observed. Hence, the proposed (Optimized BI-CNN) based image enhancement framework observes the tiny details in latent fingerprints and offers superior image structures.

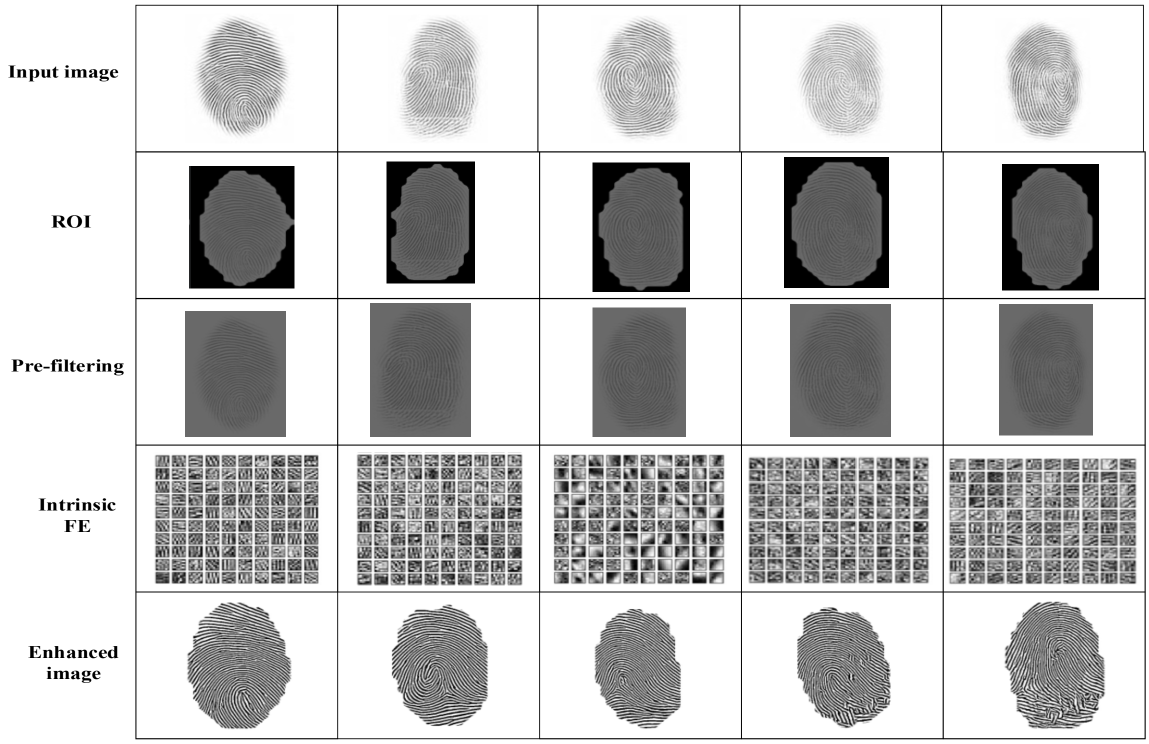


Fig 7: Experimental Outcomes on Image Enhancement (IIITD – MOLF)

Fig. 7 specifies the experimental outcomes on image enhancement obtained from IIITD-MOLF. Here, 5 sample images are chosen from the IIITD-MOLF database which is illustrated with its enhanced image structure. Also, the outcome based on step-by-step procedure is explained using image structures. The different image representations such as ROI, Pre-filtering, Intrinsic FE, and enhanced images are shown. However, these enhanced image structures helps in recognizing the image quality improvement.

Sl. No.	Name of the Method	Computation Speed (sec)
1.	ADTV	58.2
2.	Localized Dictionary	8.6
3.	FingerNet	0.7
4.	Optimized BI-CNN (Proposed)	0.642

Table 3: Comparison on computation speed

Table 3 defines the computation speed comparison on different methods. The existing approaches used for comparison are the ADTV, Localized Dictionary, and FingerNet [Li *et al.* (2018)] models. The proposed (Optimized BI-CNN) model achieved superior computation speed (0.642 sec) for test0ing a single fingerprint image compared to other methods. Hence, the proposed (Optimized BI-CNN) model attained an inference speed of (0.642 sec) which makes the matching time more effective with the existence of fingerprints of larger scale.

Enhancement	Feature+Match	Rank-25 Accuracy	Rank-50 Accuracy
BICNN	ABR11+MCC	27.33%	32.0%
BICNN	MINDTCT+MCC	30.66%	34.66%
BICNN with Pre-filtering	ABR11+MCC	32.0%	36.66%
BICNN with Pre-filtering	MINDTCT+MCC	34.0%	35.33%
BICNN+GAT	ABR11+MCC	34.33%	37.33%
BICNN+GAT	MINDTCT+MCC	34.66%	38.0%
BICNN+GAT with Pre-filtering	ABR11+MCC	36.66%	40.0%
BICNN+GAT with Pre-filtering	MINDTCT+MCC	39.33%	42.66

Table 4: Comparative Analysis of Proposed Model (MOLF database)

Table 4 describes the comparative analysis of the proposed model. The latent fingerprint recognition performance greatly depends on the minutiae points' extraction principle. The proposed (Optimized BI-CNN) enhancement method is tested under different combinations with dual publicly available feature extractors such as ABR11 (Hybrid shape and orientation descriptor) [Abraham *et al.* (2011)], MINDTCT (Miniature features or minutiae detector) [Ko (2007)]. In order to perform matching performance, a matcher named MCC (Minutia cylinder-code) is used along with the two feature extractors.

Enhancement	Feature+Match	Rank-25 Accuracy	Rank-50 Accuracy
Raw	ABR11+MCC	3.07%	5.45%
Raw	MINDTCT+MCC	8.02%	12.59%
GCN	ABR11+MCC	16.14%	22.36%
GCN	MINDTCT+MCC	12.55%	18.36%
GAN	ABR11+MCC	N/A	28.18%
GAN	MINDTCT+MCC	N/A	35.66%
Proposed	ABR11+MCC	34.66%	40.0%
Proposed	MINDTCT+MCC	39.33%	42.66%

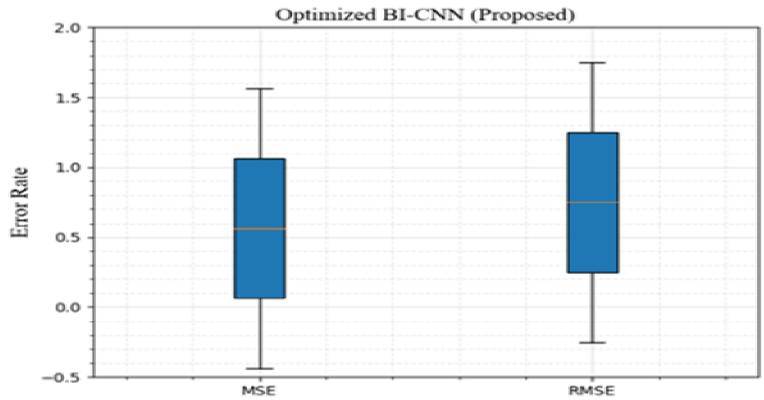
Table 5: Comparative Analysis of Proposed Model with Other Models (MOLF database)

Table 5 illustrates the comparative analysis of proposed model with other models on MOLF database. The proposed (Optimized BI-CNN) Model is compared with other models in terms of Rank-25 accuracy and Rank-50 accuracy. The proposed model on rank-25 and rank-50 accuracy with the dual feature and matching technique is compared with the performance on raw image, GCN (Generative Convolutional Networks) [Svoboda *et al.* (2017)] GAN (Generative Adversarial Networks) [Joshi *et al.* (2019)] on rank-25 and rank-50 accuracy.

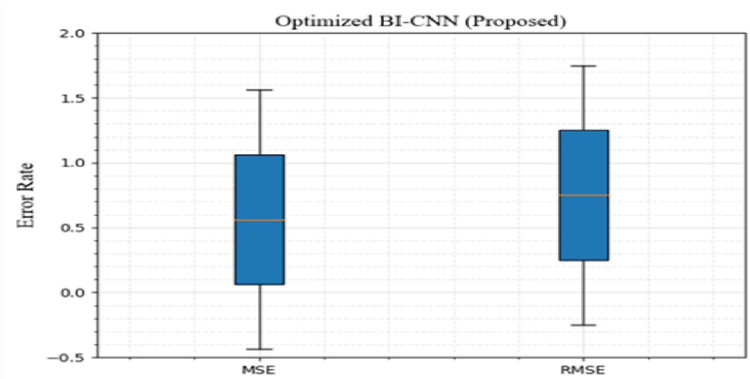
Method		Accuracy (%)	
Enhancement	Extract + Match	Rank-1 (%)	Rank-10 (%)
Raw	ABR11+MCC	35.58%	58.27%
GCN	ABR11+MCC	57.12%	79.04%
Proposed	ABR11+MCC	61.67%	83.33%

Table 6: Comparative Analysis of Proposed Model with Other Models (IIITD latent database)

Table 6 denotes the comparative analysis of proposed model with other models on the IIITD latent database. The proposed (Optimized BI-CNN) Model is compared with other models in terms of Rank-1and Rank-10 accuracy. The proposed model on rank-1 and rank-10 accuracy with the dual feature and matching technique is compared with the performance on raw image, GCN (Generative Convolutional Networks) [Svoboda *et al.* (2017)] on rank-1 and rank-10 accuracy. Hence, the proposed (Optimized BI-CNN) Model obtained higher results on both rank-1 and rank-10 accuracy.



(a)



(b)

Fig 8 (a) and (b):Error rate on IIITD-latent fingerprints and

MOLF database

Fig 8 depicts the Box-plot representation on performance measures. The proposed model (Optimized BI-CNN) based latent fingerprint image enhancement is evaluated by means of the measures such as MSE, PSNR and RMSE. Fig 8(a) illustrates the performance on IIITD-latent fingerprints database whereas Fig 8(b) shows the error performance with IITD-MOLF database. However, the Optimized BI-CNN model evaluated on IIITD-latent fingerprints achieved the error measure with MSE (0.56225) and RMSE (0.7498) while the proposed (optimized BI-CNN) model attained MSE (0.572) and RMSE (0.756) values.

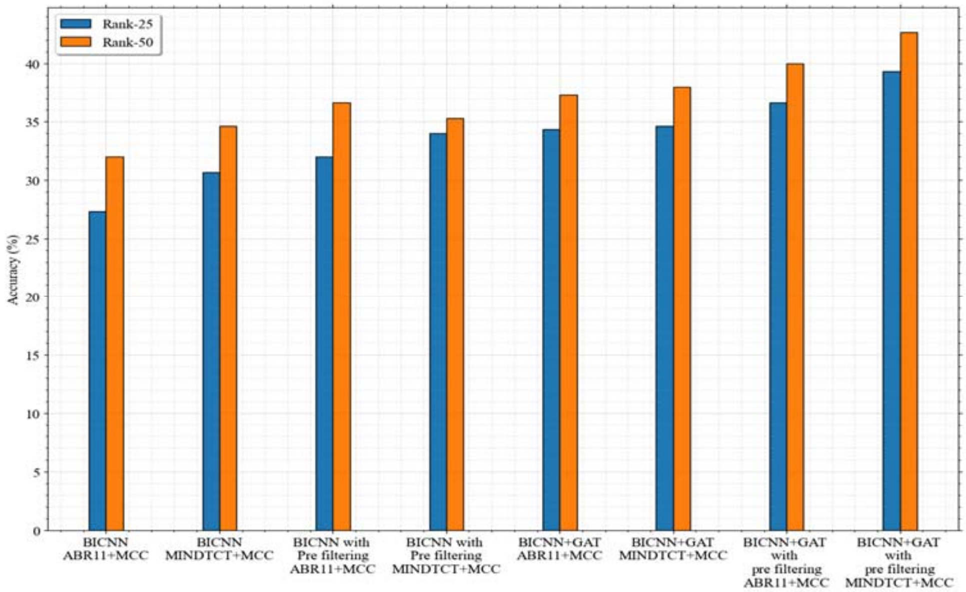


Fig 9: Ranking accuracy on proposed model

Fig. 9 describes the ranking accuracy on proposed model. The ranking accuracy for 25 and 50 on the proposed (Optimized BI-CNN) model on each stage is compared with the features such as ABR11 matched with MCC and MINDTCT matched with MCC. From the plot, it is evaluated that the proposed (Optimized BI-CNN) attained 39.33% accuracy on rank -25 and 42.66% accuracy on rank-50 with MINDTCT+MCC whereas the proposed model on ABR11+MCC obtained 34.66% accuracy on rank -25 and 40.0% accuracy on rank-50.

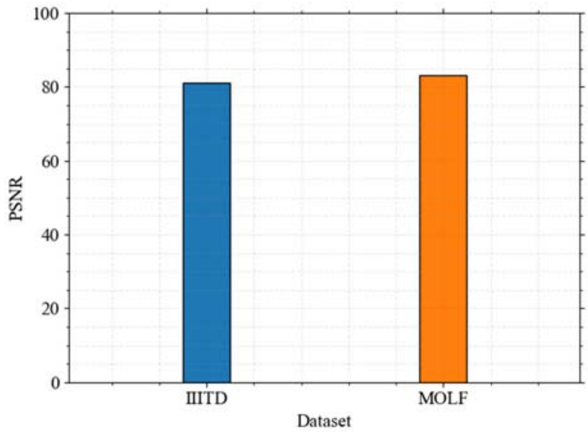


Fig 10: Evaluation on PSNR

Fig 10 illustrates the outcome on PSNR metric. The results obtained on both the datasets are plotted in terms of bar-graph. For IIITD-latent fingerprint database the value attained using the quality assessment metric PSNR is 82.39 and using IIITD-MOLF database the PSNR value obtained is 83.14 Both these values illustrates the enhanced latent fingerprint image quality.

5. Conclusion

In this work, an Optimized BI-CNN model is introduced to perform image enhancement in latent fingerprint images. In AFIS, latent image enhancement plays a major role. Enhancing the quality of latent fingerprints is still a challenging task compared to rolled and plain fingerprints. This difficulty is caused due to the presence of structured noise and low quality. A new architecture based on deep learning called Optimized BI-CNN with SPMP pooling strategy is introduced in this work for feature extraction. Next, the self-similarity is performed using GAT model that helps to get better image structure. In order to eliminate the image artifacts, reconstructing the image are performed which enhances the ridges of low clarity and predicts the information present in the ridges accurately. Finally, a feedback module is used to transform the LR images into HR images which signifies the enhanced output image. The performance of the Optimized BI-CNN (Proposed) model is demonstrated on the IIITD -latent fingerprint and MOLF database. The measures namely MSE, RMSE, PSNR, Matching and Ranking accuracy are employed to evaluate the performance of proposed framework. The outcome of PSNR metric (82.39) on IIITD -latent fingerprint as well as IIITD-MOLF PSNR (83.14) defines the superior quality of the enhanced image. Also, the IIITD -latent fingerprint database obtained 83.33% on Rank-10 accuracy and 39.33% on Rank-25 accuracy. In future, this work can be extended by considering the overlapped latent fingerprints and performing classification using hybrid deep learning models.

References

[1] Abraham, J., Kwan, P., & Gao, J. (2011). Fingerprint matching using a hybrid shape and orientation descriptor. State of the art in Biometrics, 25-56.
[2] Baig, A. R., Huqqani, I., & Khurshid, K. (2015, November). Enhancement of latent fingerprint images with segmentation perspective. In 2015 11th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS) (pp. 132-138). IEEE.
[3] Cao, K., & Jain, A. K. (2018). Automated latent fingerprint recognition. IEEE transactions on pattern analysis and machine intelligence, 41(4), 788-800.
[4] Cao, K., Liu, E., & Jain, A. K. (2014). Segmentation and enhancement of latent fingerprints: A coarse to fine ridgestructure dictionary. IEEE transactions on pattern analysis and machine intelligence, 36(9), 1847-1859.
[5] Chaidee, W., Horapong, K., & Areekul, V. (2018, February). Filter design based on spectral dictionary for latent fingerprint pre-enhancement. In 2018 International Conference on Biometrics (ICB) (pp. 23-30). IEEE.
[6] Chaudhary, N., Singh, H. P., & Dimri, P. (2020). Comparative Study of Latent Fingerprint Image Segmentation Techniques Based on Literature Review. Ambient Communications and Computer Systems, 391-399.
[7] Choi, H., Boaventura, M., Boaventura, I. A., & Jain, A. K. (2012, September). Automatic segmentation of latent fingerprints. In 2012 IEEE Fifth International Conference on Biometrics: Theory, Applications and Systems (BTAS) (pp. 303-310). IEEE.
[8] Dabouei, A., Kazemi, H., Iranmanesh, S. M., Dawson, J., & Nasrabadi, N. M. (2018, October). ID preserving generative adversarial network for partial latent fingerprint reconstruction. In 2018 IEEE 9th International Conference on Biometrics Theory, Applications and Systems (BTAS) (pp. 1-10). IEEE.
[9] Deerada, C., Phromsuthirak, K., Rungchokanun, A., & Areekul, V. (2019). Progressive focusing algorithm for reliable pose estimation of latent fingerprints. IEEE Transactions on Information Forensics and Security, 15, 1232-1247.
[10] Deshpande, U. U., Malemath, V. S., Patil, S. M., & Chaugule, S. V. (2020). Automatic latent fingerprint identification system using scale and rotation invariant minutiae features. International Journal of Information Technology, 1-15.
[11] Ezeobiejesi, J., & Bhanu, B. (2017). Latent fingerprint image segmentation using deep neural network. In Deep Learning for Biometrics (pp. 83-107). Springer, Cham.
[12] Ezeobiejesi, J., & Bhanu, B. (2018, October). Patch based latent fingerprint matching using deep learning. In 2018 25th IEEE International Conference on Image Processing (ICIP) (pp. 2017-2021). IEEE.
[13] Fan, Q., Hou, F. H., & Shi, F. (2020). Bent Identity-based CNN for Image Denoising. Journal of Applied Science and Engineering, 23(3), 547-554.
[14] Gardner, S. J., Cordingley, T. H., & Francis, S. C. (2016). An investigation into effective methodologies for latent fingerprint enhancement on items recovered from fire. Science & Justice, 56(4), 241-246.
[15] Joshi, I., Anand, A., Vatsa, M., Singh, R., Roy, S. D., & Kalra, P. (2019, January). Latent fingerprint enhancement using generative adversarial networks. In 2019 IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 895-903). IEEE.
[16] Kekre, H. B., & Bharadi, V. A. (2009, December). Fingerprint orientation field estimation algorithm based on optimized neighborhood averaging. In 2009 Second International Conference on Emerging Trends in Engineering & Technology (pp. 228-234). IEEE.
[17] Khan, T. M., Bailey, D. G., Khan, M. A., & Kong, Y. (2017). Efficient hardware implementation for fingerprint image enhancement using anisotropic Gaussian filter. IEEE Transactions on Image processing, 26(5), 2116-2126.
[18] Ko, K. (2007). User's guide to nist biometric image software (nbis).
[19] Li, J., Feng, J., & Kuo, C. C. J. (2018). Deep convolutional neural network for latent fingerprint enhancement. Signal Processing: Image Communication, 60, 52-63.
[20] Liban, A., & Hilles, S. M. (2018, July). Latent fingerprint enhancement based on directional total variation model with lost minutiae reconstruction. In 2018 International Conference on Smart Computing and Electronic Enterprise (ICSCEE) (pp. 1-5). IEEE.
[21] Liu, M., Chen, X., & Wang, X. (2014). Latent fingerprint enhancement via multi-scale patch based sparse representation. IEEE Transactions on Information Forensics and Security, 10(1), 6-15.
[22] Manickam, A., Devarasan, E., Manogaran, G., Priyan, M. K., Varatharajan, R., Hsu, C. H., & Krishnamoorthi, R. (2019). Score level based latent fingerprint enhancement and matching using SIFT feature. Multimedia Tools and Applications, 78(3), 3065-3085.
[23] Qian, P., Li, A., & Liu, M. (2019, June). Latent fingerprint enhancement based on DenseUNet. In 2019 International Conference on Biometrics (ICB) (pp. 1-6). IEEE.
[24] Sankaran, A., Pandey, P., Vatsa, M., & Singh, R. (2014, September). On latent fingerprint minutiae extraction using stacked denoising sparse autoencoders. In IEEE International Joint Conference on Biometrics (pp. 1-7). IEEE.
[25] Sankaran, A., Vatsa, M., & Singh, R. (2014). Latent fingerprint matching: A survey. IEEE Access, 2, 982-1004.
[26] Singla, N., Kaur, M., & Sofat, S. (2020). Automated latent fingerprint identification system: A review. Forensic science international, 309, 110187..
[27] Srisutheenon, K., Phromsuthirak, K., & Areekul, V. (2019, December). Semi-automatic progressive enhancement for latent fingerprints. In 9th International Conference on Imaging for Crime Detection and Prevention (ICDP-2019) (pp. 62-67). IET.
[28] Svoboda, J., Monti, F., & Bronstein, M. M. (2017, October). Generative convolutional networks for latent fingerprint reconstruction. In 2017 IEEE International Joint Conference on Biometrics (IJCB) (pp. 429-436). IEEE.
[29] Tang, Y., Gao, F., & Feng, J. (2017, October). Latent fingerprint minutia extraction using fully convolutional network. In 2017 IEEE International Joint Conference on Biometrics (IJCB) (pp. 117-123). IEEE.

[30] Wang, Y., Wang, J., Ma, Q., Li, Z., & Yuan, Q. (2018). Recent progress in background-free latent fingerprint imaging. Nano Research, 11(10), 5499-5518.
[31] Xu, M., Feng, J., Lu, J., & Zhou, J. (2017, September). Latent fingerprint enhancement using Gabor and minutia dictionaries. In 2017 IEEE International Conference on Image Processing (ICIP) (pp. 3540-3544). IEEE.
[32] Zhang, J., Lai, R., & Kuo, C. C. J. (2013). Adaptive directional total-variation model for latent fingerprint segmentation. IEEE Transactions on Information Forensics and Security, 8(8), 1261-1273.
[33] Zhang, L., Yuan, H. W., & Li, X. M. (2018). Active polarization imaging method for latent fingerprint detection. Optical and Quantum Electronics, 50(9), 1-12.
[34] Zou, J., Feng, J. B., Zhang, X. M., & Ding, M. Y. (2013). Local orientation field based nonlocal means method for fingerprint image de-noising. Journal of Signal and Information Processing, 4(3B), 150.

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