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ORIGINAL RESEARCH

A Robust Deep Features Enabled Touchless 3D-Fingerprint Classification System

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Abstract

The exponential rise in software computing and hardware technologies has broadened the horizon for different applications in decision making to make human life efficient. Among all the major demands, security systems have always been the dominant one to ensure authenticity of data, source or certain activity. Fingerprint technology has gained wide-spread attention for personalized data, resource or activity accesses authentication. Though, numerous methods have been developed for fingerprint detection and identification, the local input environment, data suitability, distortion and hardware dependency have been the challenge to yield optimal performance. On contrary, the possibilities of touchless 3D-fingerprint identification systems have attracted scientific communities due to ease of implementation, reduced dependency on local environment and sensing hardware. In this paper deep features-based Touchless 3D-Fingerprint Classification System is proposed. In this model a transfer deep-learning model AlexNet-CNN is used for deep feature extraction and classification, which obtains 4096 dimensional deep features. The proposed approach achieves a classification accuracy of 90.20%.

Keywords 3D Fingerprint · Touchless · Deep learning · Convolutional Neural Network · AlexNet · Transfer learning

Introduction

In the last few years, the advances in computer vision and hardware technologies have broadened the horizon for different application environment to make optimal decisions such as access authentication or security systems. Among the different innovations towards access control and security, fingerprint detection and classification system which exploits biometric traits has been applied extensively across different domains [1]. In general, the classical fingerprint systems employ touch-based image acquisition devices like optical sensor or solid-state image sensors. However, these classical approaches often undergo adversaries due to hardware dependencies and local environmental defects [2] and different adverse conditions such as fingerprint sample distortions, scratches or physical damages, low contrast regions, humidity and dirty samples, loss of latent information. Unlike classical fingerprint approaches, Touchless approaches seem to be promising and more efficient as it can alleviate the problem of contact with fingertip with acquisition surface. Additionally, it can also avoid probability of transmission of pandemic disease like COVID19 and other skin-disease transmission. Touchless method also reduces acquisition time and user training demands. However, the detection, identification and interoperability are inferior to the classical touch-based approaches, which are undeniably more constrained, expensive and bulkier. Touchless fingerprint systems function on the basis of 3D mechanisms which typically retrieve higher accuracy in comparison to the methods based on single images as it can enable more robustness to deal with perspective distortions. Additionally, 3D methods can obtain supplementary features from 3D-fingerprint shapes. In the last few years, efforts have been made to exploit hand-based traits using sophisticated

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Touchless acquisition and 3D models. A few methods are hand geometry [3], palm-print [4], finger geometry [5], and knuckle-print [6]. To reduce acquisition constraints authors have used Touchless manner. The dominating examples are face [7], iris [8], gait [9], and ear [10]. In major Touchless approaches employing finger and hand features, the input-instances or samples are retrieved without controlling user's posture. Consequently, it can cause low quality, view-point distortions, and non-linear resolution. Thus, the majority of the biometric systems employ certain calibrated rules and guides to place gesture or human-body part to make identification. Some of the efforts which avoid placement guides are fingerprints [11, 12], hand surface placement [3], and finger shape [13]. The major fingerprint detection models are developed based on 2D input acquisition, on contrary 3D features could enable both cost-effective and unconstrained security solution. However, achieving an optimal solution requires better input environment, data processing, multiple viewpoints-based ROI detection and feature learning, followed by a robust classification [14].

Considering above stated discussion and scopes, in this paper a robust deep feature enabled deep-learning model for Touchless 3D-fingerprint classification system has been proposed. This approach can be computationally more efficient and constrained as compared to conventional methods in [15], as it avoids iterative user involvement and acquisition interface or surface. In the proposed method, the finger can be placed with varied 3D orientation as long as the sufficient area of the ridge pattern is visible. Unlike majority of the existing approaches where authors have applied photometric stereo approach by considering multiple images from different orientations are used; the proposed model avoids such dependency but employs two images with random movement of fingerprint to perform identification or classification. Realizing the significance of a robust and accurate Touchless 3D-fingerprint classification model, the proposed method employs a transfer deep learning-based model. In this approach, a transfer learning-based method named AlexNet-CNN has been used to extract high dimensional (here, 4096 dimensional) features followed by classification. Simulation has exhibited that the proposed approach achieves an accuracy of 90.6%.

Related Work

This section is mainly about discussion of some of the key recent literatures pertaining to fingerprint detection and classification. Khan et al. [16] developed singular points extraction to enable computationally efficient fingerprint recognition. However, authors could not address different input conditions such as variation in ridge feature and illumination which is common in 3D-fingerprint detection approaches. To enhance classification accuracy, Jain et al. [17] recommended dual stage classifiers. Ding et al. [18] applied Gabor filter with dictionaries learning concept to perform fingerprint detection and classification; though the classical ROI segmentation and wavelet-based model confines its robustness over complex input nature. Tan et al. [19] derived a knowledge driven model with feature-learning algorithm based on Genetic Programming (GP), which was mainly used to select features, while Bayesian classifier model was applied to perform classification. A feedback-based line-detector was developed by Shah et al. [20] to achieve better ROI detection, which was later processed for classification using SVM, K-Nearest Neighbor and Artificial Neural Network. Among the classifiers, authors found that ANN can enable higher accuracy. Halici et al. [21] applied a self-organizing feature maps (SOFM) with ANN classifier to perform fingerprint classification. Authors modified SOFM learning and ANN with "certainty" concept to deal with distorted regions of fingerprint images to enable higher accuracy. Considering skin distortion over fingerprint, Si et al. [22] at first rectified skin distortion with single fingerprint image, which was later classified using SVM.

Unlike conventional fingerprint classification goals, Mishra et al. [23] examined efficacy of different classifiers such as SVM, NN and Fuzzy-C Means (FCM) to perform gender classification. Satheesh [24] applied clustering concept to segment ROI, which was processed for classification using SVM. Unlike classical wavelet-based approaches, deep-learning concepts have gained wide-spread attention for image analysis and classification. Considering its efficacy, a few researches have been carried out using deep-learning methods for fingerprint detection and classification. Zhang et al. [26] developed a Convolutional Neural Network (CNN) based fingerprint liveness detection named Slim-ResCNN to distinguish authentic fingerprints from the fake ones. Yuan et al. [27] proposed an improved Deep CNN with image scale equalization to preserve texture information and maintain image resolution, which was trained using adaptive learning rate to perform accurate fingerprint detection and classification. Adaptive preprocessing and enhancement techniques are taken from our own previous research work, which was on verification of 3D touchless fingerprint [28]. Tertychnyi et al. [29] applied deep neural network (DNN) concept to detect the low-quality fingerprints with high accuracy and reliability. Chugh et al. [30] applied deep CNN based approach using local patch center and aligned with fingerprint minutiae to perform fingerprint classification. Wang et al. [31] proposed a fingerprint classification method based on deep-learning techniques by choosing orientation field as the classification feature. Recently, Labati et al. [32] proposed ANN approach for the estimation of image quality of the unwrapped 3D fingertip. Obtaining different set of features authors have performed fingerprint image quality assessment for better detection accuracy.

Observing above stated literatures, it can be found that undeniably numerous researches have been done towards fingerprint classification; however, majority of the existing approaches employ 2D feature set with classical wavelet analysis or ridge information. Unfortunately, these approaches cannot be suitable for Touchless verification environment. The classical fingerprint verification models are hardware or sensor dependent, while Touchless solution can alleviate such dependency and hence can be more effective for real-time security purposes. Considering it as motive, in this paper the focus is made on developing a robust 3D Touchless fingerprint classification system.

System Model

The proposed method can be visualized as a four phased implementation that comprises of Data Acquisition, Preprocessing and AlexNet-CNN based Feature Extraction followed by classification as shown in Fig. 1. The detailed discussion of the proposed method and allied discussion is given in the subsequent sections.

Data Collection

Unlike majority of the existing approaches, the proposed model employs two images with random movement of fingerprint to perform classification. Input fingerprint images are obtained with different orientation or viewpoint. In other words, unlike classical 2D based models where acquisition surface is applied, here a multi-view Touchless fingerprint images with 3D data model is used, provided ridge information is visible. Here a set of Touchless fingerprint images were obtained by placing the finger randomly in front of camera with different 3D orientation provided the sufficient area of the ridge pattern remains visible. In the proposed method, data samples from 1000 random users are collected from different benchmark databases. (Hong Kong Polytechnic University 3D-fingerprint images Database Version 2.0, IIT Bombay, Touchless Fingerprint Database", "UNFIT database" Image Analysis and Biometrics Lab. IIT Jodhpur. Where for each user or participant a set of images captured at different orientation and viewpoints are considered. The input images are obtained in *.BMP format as well as *PNG. Multi-view inputs have been obtained for each participant, and thus a total of 2000 input images with two different viewpoints and local environment (different light conditions, contrast or quality) were obtained for further process.

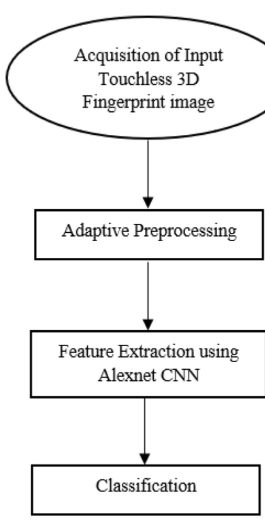


Fig. 1 Framework of the proposed system

Preprocessing

Understanding the difficulties in case of Touchless image acquisition such as non-uniformity in lighting conditions, variations in intensity, contrast and quality variations. So, it is necessary to process need to process each input sample with pre-processing techniques. First, images are processed for image resizing. Unlike classical methods to retain maximum possible ridge information where the dimension is static and predefined, here adaptive resizing is performed in the proposed method where at first centroid of the fingertip images is obtained. With the centroid information obtained a radius of 120 pixels with reference to that is drawn thus a circular ROI was obtained for each image.

After obtaining the Region of interest, it is processed for RGB to GRAY conversion. Over Grayscale output an adaptive histogram equalization is performed that solves major problems of variation in intensity and makes it suitable for further processing. In the proposed method, the gray-level range is expanded to the histogram maxima which results in better feature detection ability. This is because of the improved contrast. Noticeably, in this case the probability density function (PDF) of each pixel l_k is obtained using Eq. (1).

$$p_k\left(l_k\right) = \frac{mk}{m}, \tag{1}$$

where, $0 \leq l_k \leq 1, k = 0,1, \ldots, 255$ and m_k signifies the number of pixels at l_k, while m being the total number of pixels.

Equalization is then followed by normalization of the image, which enables spreading the gray scale values evenly across image and fill all accessible image parts. To perform normalization of input at first, the highest and the lowest pixel values for the processed input is obtained. Thus, with the obtained pixel-intensity values image-normalization is performed using Eq. (2)

$$I_{\mathrm{Norm}}(x,y) = \frac{I(x,y) - I_{\min}}{I_{\max} - I_{\min}} \times M. \tag{2}$$

In Eq. (2), the parameter I signifies the Gray level intensity of the fingerprint image, while $I_{\min}$ and $I_{\max}$ states the minimum and the maximum intensity values, respectively. The variable M states the new highest value of the scale, which is often selected as 255, which results into 256 distinct Gray levels. $I_{\mathrm{Norm}}(x,y)$ presents the normalized pixel value with x and y dimensions. Thus, with normalization it becomes easier to assess image quality as well as key features to make further process. Since in Touchless fingerprint images, there can be the presence of noise components due to finger-orientation inconsistency and even noise due to 3D-fingerprint sensor. The proposed method applies ridge-orientation feature that enables image-filtering in the direction of ridge. This approach can reduce ridge noise significantly by obtaining Gray scale gradient which is nothing but a vector with orientation signifying the direction of the steepest change in the Gray scale values.

After performing RGB to Gray conversion and subsequent process of adaptive histogram equalization, normalization and filtering, a binarization process is performed that distinguishes ridge from background by converting Gray scale image into binary picture. Noticeably, binary picture possesses two distinct values, black and white signifying 0 and 1, respectively. In the proposed method, an Adaptive Thresholding assisted 3D-fingerprint image transformation and Binarization is applied. This method selects the threshold on the basis of the local mean intensity, which is often called as the first-order statistics in the vicinity of each pixel. Unlike classical adaptive thresholding methods, here a adaptive threshold estimation with 0.5 sensitivity factor is performed, (which signifies sensitivity towards thresholding more pixels as foreground). It enables retrieving maximum possible ridge information and structural information to support better accuracy.

To obtain the adaptive threshold, the Gray scale fingerprint image and its 3D volume is converted into equivalent binary image by binarization. Here, threshold is applied as a global image threshold which has been characterized as a scalar luminance value or matrix of luminance values of each pixel over targeted ROI. The binary image is obtained from Eq. (3).

$$I_{\mathrm{bin}}(m_1, m_2) = \begin{cases} 1, & \text{if } I_{\mathrm{old}}(m_1, m_2) \geq \text{Local Mean} \\ 0, & \text{Otherwise} \end{cases}. \tag{3}$$

Obtaining the binary image of the fingerprint, thinning is performed that enabled skeleton formation. In this method for each input binary image, ridges were presented as a thin single-pixel wide presentation without changing the overall fingerprint pattern. Thinning is done in such a manner that it maintains gaps between different ridges, representing a structural skeleton. This process enabled our proposed model in achieving efficient feature estimation as well as redundant data elimination that makes overall process computationally efficient. The images obtained after preprocessing of touchless 3D-fingerprint image are shown in Fig. 2.

AlexNet-CNN-based Fingerprint Feature Extraction and Classification

AlexNet is a recently developed CNN within possesses the high robustness and computational efficacy to perform object detection and classification tasks. However, it has been mainly employed for image classification purposes. The robustness of AlexNet-CNN is its ability to be transformed to cope up with different data and deep-learning structures to perform deep feature extraction and classification. The proposed method uses AlexNet-CNN as a feature extraction model which obtains high dimensional features with 4096 dimensional-kernels at the fully connected (FC) layers. In the proposed method a modified pretrained AlexNet-CNN (trained with ImageNet database designed by academics intended for research) is trained with touchless 3D-fingerprint images (70% of the database is used for training and remaining 30% is kept for validation). For implementation of the proposed method a pre-processed fingerprint input with image resizing and ROI estimation (Fig. 2d) is applied as input to the first layer of Alexnet CNN with image size of $227 \times 227 \times 3$ which has been further processed for feature

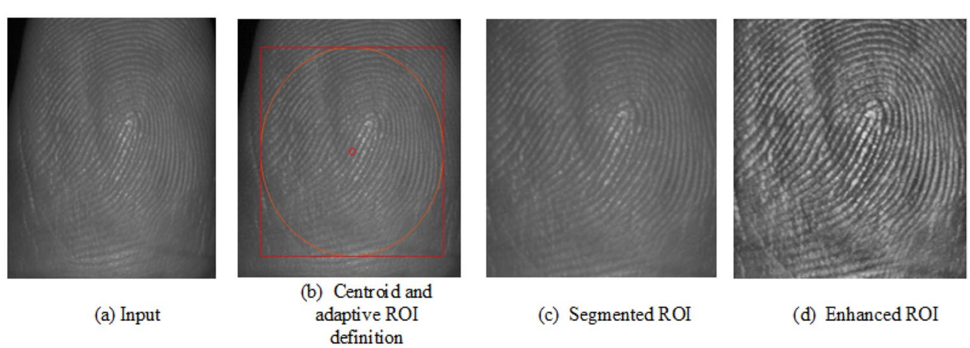


Fig. 2 Touchless Input and pre-processed data

extraction followed by classification. The structural schematic of the modified AlexNet-CNN model is given in Fig. 3. Noticeably, the use of high dimensional features with 4096-kernels can provide optimal deep features to achieve high accuracy and reliability.

As depicted in Fig. 3, modified AlexNet-CNN model encompasses five Convolutional layers (i.e., CONV1, CONV2, CONV3, CONV4 and CONV5) and three Fully Connected Layers (FC6, FC7 and FC8). In addition, two max-pool layers are used as well. Some of the key structural parameters considered in the proposed AlexNet-CNN model for fingerprint feature extraction and classification are given in Table 1.

A brief of the AlexNet design considered in this research is given in the subsequent sections.

Input Layer

In AlexNet-CNN the 3D Touchless fingerprint image is given as input. Noticeably, before feeding input data to AlexNet, the proposed method performs image resizing, RGB to GRAY, ROI segmentation and image enhancement as pre-processing. Once obtaining the pre-processed fingerprint data (Fig. 2d), it is fed as input to the AlexNet-CNN that generates features at the CONV layer, which is further followed by Max-Pooling (functions as feature consolidation or selection). To achieve better performance, a feature scaling and mean subtraction methods are used, where the input images which are already processed for resizing to $227 \times 227 \times 3$ dimension are fed as input of the subsequent CONV layer. A brief of the AlexNet-CNN convolutional layer is given as follow.

Convolutional Layers

Convolutional Layer can be called as the combination of filters which can extract specific patterns from the input fingerprint images. Here, CONV obtains the features from the input images (shown in Fig. 4c) which are retrieved as the output and states the feature map signifying specific fingerprint and allied ridge features. Here, each neuron in the extracted feature map share similar set of weights (W) and

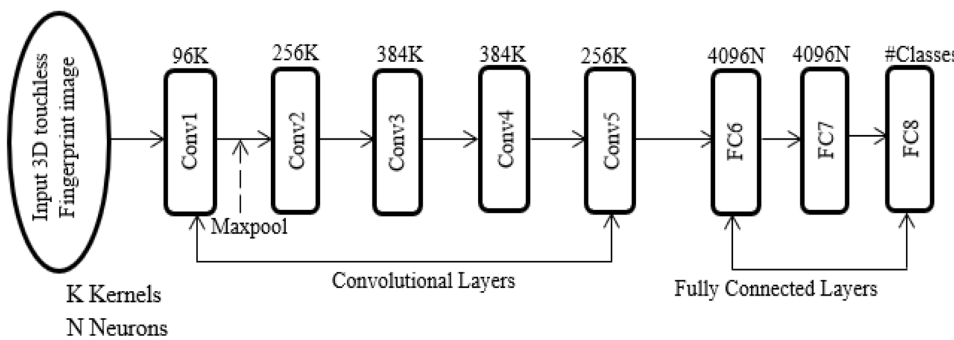
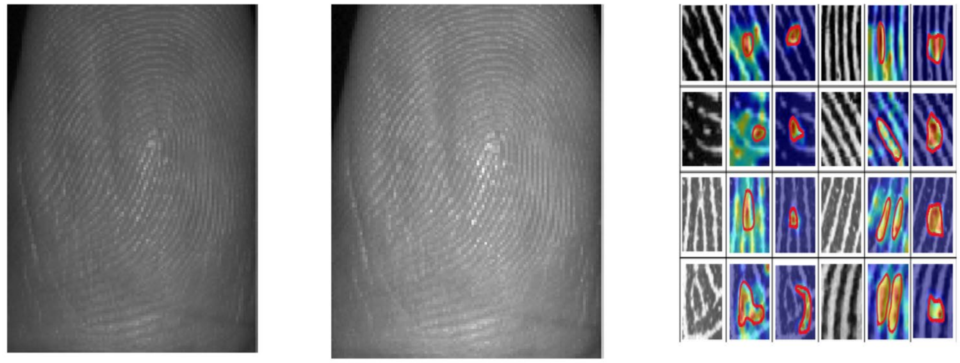


Fig. 3 AlexNet-CNN architecture

Table 1 Proposed modified transferable CNN structure

Layer	Layer name	Specific operation
1	Image Input	$227 \times 227 \times 3$ with zero-center normalization
2	Convolution (CONV1)	96 $11 \times 11 \times 3$ convolutions with stride [4 4] and padding [0 0 0 0]
3	ReLu	ReLu
4	Convolution (CONV2)	2 groups of 128 $5 \times 5 \times 48$ convolutions with stride [1 1] and padding [2 2 2 2]
5	ReLu	ReLu
6	Max-Pooling	3×3 Max-Pooling with stride [2 2] and padding [0 0 0 0]
7	Convolution (CONV3)	384 $3 \times 3 \times 256$ convolutions with stride [1 1] and padding [1 1 1 1]
8	Convolution (CONV4)	2 groups of 192 $3 \times 3 \times 192$ convolutions with stride [1 1] and padding [1 1 1 1]
9	Convolution (CONV5)	2 groups of 128 $3 \times 3 \times 192$ convolutions with stride [1 1] and padding [1 1 1 1]
10	Fully connected (FC)	3 FC layers (FC6, FC7 and FC8)
11	ReLu	ReLu
12	Drop-out	50%
13	Learning rate	0.0001
14	Learning method	ADAM
15	Number of epoch	50

Fig. 4 Extracted features



(a) Input touchless fingerprint (b) Normalized image (c) Extracted feature

bias (b) values, which enables neurons to detect the similar features. Similarly, other feature maps in CONV use varied sets of biases and weights to assist different local feature extraction. In AlexNet-CNN, CONV layer filters the input images to calculate a single feature map as output. Here, AlexNet-CNN contains five CONV layers including CONV1, CONV2, CONV3, CONV4 and CONV5 with zero-padding. The stride of the CONV layer is maintained as 4. Noticeably, the kernel specification at CONV layer is CONV1-96 kernels, CONV2-256 kernels, CONV3-384 kernels, CONV4-384 kernels and CONV5-256 kernels. The touchless input fingerprint image, normalized fingerprint and its extracted feature using AlexNet-CNN are depicted in Fig. 4.

Max-Pooling Layers

Max-pooling layer acts as feature selection layers where it reduces the spatial resolution of each feature map obtained from CONV layer. Additionally, it intends to minimize the total number of parameters that makes computation better and efficient. It achieves it by reducing computation cost during local averaging and a sub-sampling and hence strengthens it to avoid over-fitting problem. In the proposed structure, the Max-pooling is used as default structure of CNN to retain translation-invariant representations in fingerprint images. Here, Max-pooling down-samples the latent representation using a constant component by employing the highest value over non-overlapping sub-space. It considers sparsity over the hidden representation by eradicating all non-maximal values in non-overlapping sub-space. It enhanced the efficacy of proposed transfer learning model and feature detection model to avoid insignificant solutions for getting carry forward, which can impose computational overhead. Functionally, in the proposed AlexNet-CNN model, one Max-pooling layer after each CONV layer is used, where each layer is defined for 3×3 receptive field with a stride of 2. Here, the receptive filed signifies spatial extent which is achieved by means of classical Max-operation for the defined spatial extent.

ReLu Layers

In the proposed transfer learning model, a supplementary layer known as ReLu is used that primarily acts as an activation function. ReLu layer contains a non-linear element-wise operator function as a layer. Here, three ReLu layers, where with input y, it estimates the output for the neuron $q(y)$ as y if $y > 0$ and $(\delta \times \mathrm{y})$ if $y \leq 0$. Here, δ signifies whether the negative component is required to be ignored by means of multiplication with a slope (Ex. 0.01…) or fixing it to 0. In the proposed AlexNet-CNN model ReLu function $q(y) = \max(0, y)$ at zero threshold value is performed.

Fully Connected Layers

In CNN, FC layers functions at the end of the structure where it exhibits high-level reasoning to make classification. Because of this reason it is named as classifier layer of CNN. In function, it receives a set of feature vectors from the previous layer and maps it to the connected neurons that finally generates a one-dimensional vector and labels each input image by its class (here about 1000 classes) by considering millions of parameters (up to 61 million parameters in the proposed method).

Results and Discussion

Considering the significance of a robust and efficient touchless 3D-fingerprint detection and identification system, in this research a multi-dimensional optimization measure is developed where focused on at first enabling a sound data environment with multi-view inputs, followed by feature

Table 2 Comparative summary of performance from contactless 3D-fingerprint classification methods

Classification methods	Validation Accuracy (%)
Minutiae-SSIM [28]	90.02
Proposed Touchless 3D-fingerprint classification system using Alexnet	90.20
Fine-tuned single channel multi view [33]	85.40

extraction mechanism and classification. Realizing the complexity of touchless 3D input images, at first, camera is used for input acquisition in such a manner that it retains maximum possible ridge information. Being a touchless model, which is a multi-view input enabled by retaining more fingerprint information yields optimal performance. Realizing the fact that the touchless data acquisition might undergo different local environment changes such as illumination change, contrast variation and skin-surface defects, a robust pre-processing is performed includes RGB to Gray, normalization, filtering and enhancement. The prime objective of this phase is to ensure suitable data environment for further computation. The proposed method uses AlexNet-CNN for high dimensional feature extraction. Noticeably, to perform learning over the extracted feature the learning rate of 0.0001 is maintained, where steepest gradient descent model (SGDM) with entropy classifier has been applied and prediction is performed. The conventional approach [28] majorly extract minutiae using crossing number concept method and minutiae features are matched with the reference fingerprint images using pattern recognition techniques like Structural Similarity index matching. Lin and Kumar [33] address challenging contactless partial 3D-fingerprint identification problem. The proposed method shows better results compared to the stated conventional methods. The comparative results are shown in Table 2. Thus, the proposed model achieves better performance that enables it to be used for real-time application.

Conclusion

Considering the significance of a Touchless 3D-fingerprint classification system as an alternative to the classical 2D fingerprint classification approaches, in this paper a multi-level optimization measure is proposed. Realizing the need of Touchless 3D-fingerprint classification, the enhancement has been made by pre-processing. To achieve it, at first 3D-fingerprint datasets are collected which are processed for pre-processing using image resizing, RGB to Gray conversion, morphological centroid adaptive local patch estimation, and adaptive histogram equalization. The process involved in pre-processing enables optimal process environment for Touchless computation. Followed by Multi-dimensional feature extraction with millions of parameters and classification using modified pretrained Alexnet CNN. Noticeably, the results obtained are justifiable. Thus, considering overall efficiency and robustness of the proposed system, it can be a potential alternative to the touch-based technologies for privacy and hygiene centric authorization environment during this pandemic situation.

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Declarations

Conflict of Interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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