2023 International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems (ICAECIS) | 979-8-3503-4805-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICAECIS58353.2023.10169966

Separation of Overlapped Fingerprint Images using Deep Learning

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***Abstract*—Criminal investigations have evolved with advancements in technology. Traces of fingerprints play a vital role in identifying and understanding crime scenes. These traces can form a clue to various suspects of crime. Fingerprints obtained from such crime scenes are often low quality, damaged and, most of the time, overlapped. It is a crucial requirement to separate overlapped fingerprints, which can be beneficial in identifying an individual, especially in criminal investigations, as it can approve or disapprove a person's identity. Overlapped fingerprint separation is a challenging task. Several methods have been utilized to segregate overlapped fingerprints, resulting in the successful ability of the Automated Fingerprint Identification System (AFIS) to match the individual fingerprints.**

The objective of the proposed study is to classify the fingerprint images that are overlapped and separate these images by using a deep learning approach. Further, the result is extended to reconstruct these separated fingerprint images. The experimental results show that overlapped fingerprint images are efficiently separated, but there is sufficient scope for improving the reconstructed images of the damaged part of the fingerprint image.

Keywords—fingerprint reconstruction, overlapped finger-prints, deep learning, latent fingerprint.

I. INTRODUCTION

In our daily lives, we often touch things, and when we do so, we leave our unique signatures, i.e., fingerprints. As defined by Webster, the fingerprint is nothing but an impression of a fingertip on any surface. It is a critical feature used for the identification of a person. It is a unique attribute to identify a person. Other features of a person may vary, but fingerprints do not. A fingerprint is an unalterable attribute throughout a, person's life. Such latent prints are found on various surfaces, although they are not readily visible. Detecting latent fingerprints often demands using fingerprint powder, chemicals, or equivalent light sources. The sweat of a person's body and natural oils on the skin are deposited onto another surface, causing the formation of latent fingerprints. The conventional approach to detect and collect latent fingerprints involves using fingerprint powders like black granular, black magnetic, aluminium flake, etc. to dust smooth surfaces. [1].

Fingerprints have various information like ridge count, valley area, ridge density, etc. The methods used to identify an individual's fingerprints are the formation of patterns on the fingertips or impressions made by the appearance of minute ridge. No two persons share the same arrangement of patterns present in a ridge.

Many real-time applications adopt fingerprints, such as biometric authentication systems, passport verification at the airport, person identification during the crime investigation in forensics, etc.

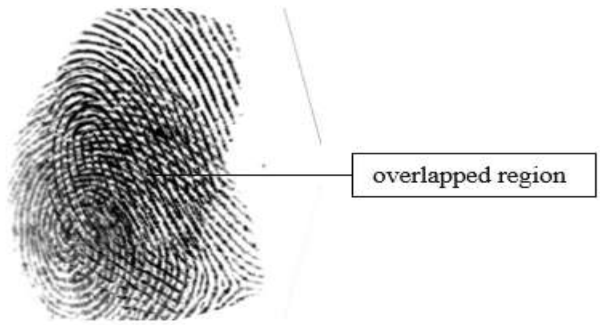

Fig. 1. A sample of overlapped fingerprint image

There are multiple ways to obtain fingerprints, preferably physical, including the inked method. The second is during a crime scene investigation. The fingerprints obtained are latent or invisible and overlapped, as shown in Fig. 1, and most of the time, we acquire a sub-part of the fingerprint. However, conventional Automated Fingerprint Identification Systems (AFIS) require separated target fingerprints [2]. In this direction, the objective of the study is to segregate merged or overlapped latent fingerprints and reconstruct those separated fingerprints that are partial by using deep learning techniques.

II. RELATED WORK

A vast community of researchers have worked on several aspects of fingerprints, right from extraction from the surface to detecting fingerprints and separating latent fingerprints.

Our work focuses on the separation of overlapped fingerprints. At latent development stages, Forensic scientists have proposed to use gold nanomaterial; however, this method has its drawback, it only works for a specific type of latent overlapped- fingerprints, where part of a fingerprints are believed to be covered with different lipids.

Fanglin Chen et.al in [3] presented an algorithm that relies on a relaxation labelling method and Gabor filtering. By using local Fourier analysis, the process begins by generating an initial orientation field for the fingerprint image that has overlapping ridges, followed by the implementation of relaxation labelling method to separate the two fingerprints. The two components are then filtered by utilizing Gabor filters that are adjusted to the component orientation fields. The algorithm has been found to give satisfactory results on latent overlapped fingerprints.

Some works in [4] and [5] are carried on fingerprint enhancement. In [4] an algorithm has been proposed based on a combination of a filter in the spatial and Fourier domain. Gabor filter is used for fingerprint enhancement due to its best frequency resolution. Such filters are used to eliminate the problem of dealing with high curvature regions. The paper [5] presents an in depth analysis of the various techniques used in AFIS, including minutiae-based, ridge-based, and correlation-based methods. It also discusses the challenges faced by researchers in developing accurate and reliable AFIS, such as the quality of the latent print, the variability of the ridge patterns, and the need for large databases of fingerprint images.

Chi Hsiao et.al in [6] employed Deep Normalization Convolutional Neural Network (DNCNN) a deep learning model using Tsinghua dataset for the separation of overlapped fingerprints. The literature describes the limitations of current biometric identification methods, which concentrate on individual fingerprint processing and do not provide adequate analysis on identifying overlapped fingerprints, which are common in criminal investigations. The authors proposed an automatic and efficient method for dealing with overlapped fingerprints using a convolutional neural network. The experimental outcomes demonstrate remarkable precision rates for both single and multi-fingerprint latent tests, as well as an accurate detection rate for the range of overlapped and non-overlapped fingerprints. The proposed method could significantly improve the efficiency of fingerprint separation work and represents an important advancement in the field of biometrics and artificial intelligence.

FinSNet model used in [7] is one of the significant works in latent fingerprint separation and a deep learning based network for separating overlapped fingerprints. The network separates the vertical and central faced fingerprint through a single flow and uses an affine transformation to place the centre and erect the target fingerprint. This transformation plays a crucial role in enabling separation by helping to differentiate between the two fingerprints. The effectiveness of the FinSNet network in segregating overlapped fingerprints has been confirmed through its verification using the Tsinghua simulated data sets for such fingerprints. The use of deep learning techniques in latent fingerprint separation is a promising development as it allows for more accurate and efficient separation of overlapped fingerprints.

For reconstruction of fingerprints, most of the researchers have used autoencoders. The paper [8] by S. Saponara et al. has experimented with CNN autoencoder and Sparse autoencoder for reconstructing fingerprints. CNN autoencoder performed much better than sparse autoencoder. Also, the CNN autoencoder emerged as suitable for running on low-cost embedded devices because of less memory usage compared to other encoders and pre-trained models.

In [9], the authors utilized asynchronous processing in order to identify latent fingerprints in CPU-GPU systems that are heterogeneous in nature. This allows for quick similarity results to be obtained between the fingerprint and latent impressions. The use of asynchronous processing in a heterogeneous system is beneficial as it allows for a more efficient use of both the CPU and GPU resources, leading to faster processing times and improved overall performance. By utilizing the strengths of both the CPU and GPU, this methodology is able to obtain quick and accurate similarity results between the fingerprint and latent impressions.

The authors in [10] proposed a model based on deep learning to detect smoke in images. The authors discuss the limitations of traditional computer vision techniques for this task and describe the architecture of their proposed model, which includes normalization layers and multiple convolutional and pooling layers. The authors assess the efficacy of their model by testing it on multiple datasets consisting of both smoke and non-smoke images. To benchmark the model's performance, they compare it with various baseline models, including conventional computer vision techniques and deep learning models that do not employ normalization layers. According to the results, the proposed model outperforms the other models in terms of accuracy and F1 score, demonstrating the effectiveness of the normalization layers in improving the performance of CNNs. The authors also discuss the limitations of their model and suggest possible directions for future research. Overall, the paper provides a comprehensive overview of smoke detection in images and proposes a new deep learning model, which utilizes normalization layers and CNNs, has been developed and demonstrates high accuracy.

The authors presented in [11] a machine learning system that deals with the challenging task of recognizing and classifying overlapped fingerprints in biometric identification. They used a dataset of 3000 fingerprint images for training and testing their system. The proposed system for recognizing and classifying overlapped fingerprints employs image processing techniques and machine learning algorithms, such as Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs). The authors achieved a classification accuracy of 94% using their system, which outperforms existing techniques for recognizing and classifying overlapped fingerprints.

The authors in [12] proposes a hybrid approach for accurate latent fingerprint segmentation using an early fingerprint distinction technique and a Stacked Convolutional Autoencoder (SCAE). The combination of SCAE and CNN provides superior feature engineering for image classification, and a pre-trained CNN with SCAE produces improved results compared to a conventional CNN. Results from experiments conducted on the IIIT-D database demonstrate that the proposed method achieves superior accuracy and efficiency compared to existing methods, with a segmentation accuracy of 98.45% on high-quality images.

III. SYSTEM ARCHITECTURE

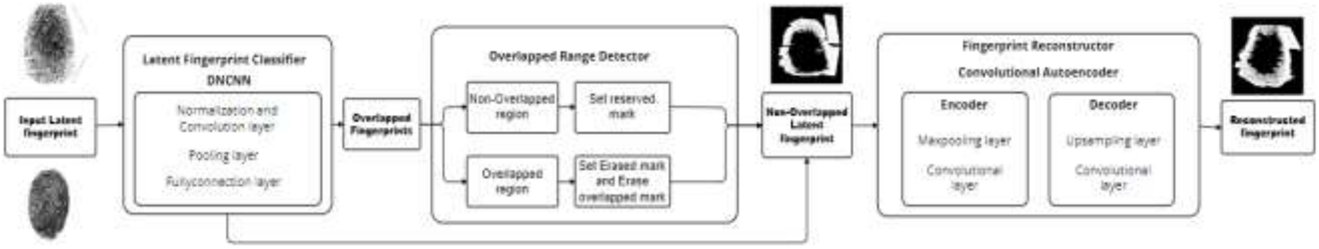

Fig. 2. Fingerprint Classifier and Reconstructor

The working of the proposed system is as shown in Fig. 2. The latent fingerprint image is an input to the system. Once the fingerprint image is loaded, preprocessing is performed. Preprocessed images produce better results than the sample images when they are applied to the different models. The input images are converted to grayscale that simplifies the module capacity and reduces computational requirements. We used patch-based image denoising approaches that can enhance images by effectively reducing noise. We then used Gaussian Noise Standard Deviation for reducing high variations.

In the preprocessing step of the overlapped range detection module, the overlapped latent fingerprint is first marked and cropped to a range using the Regionprops technique available in MATLAB. The ranges are then partitioned into a training set and a testing set. If there is a non-overlapped region, it is marked as a reserved mark, otherwise, it is marked as an erased mark. Finally, the overlapped range is erased according to the mark. This preprocessing step is important as it helps to identify and isolate the overlapped regions in the fingerprint image, which are then used for further processing and separation.

Further, the image is reconstructed using a convolutional autoencoder. If there is no overlapped region, then simply the reconstruction is performed.

A. *Latent Fingerprint Classifier*

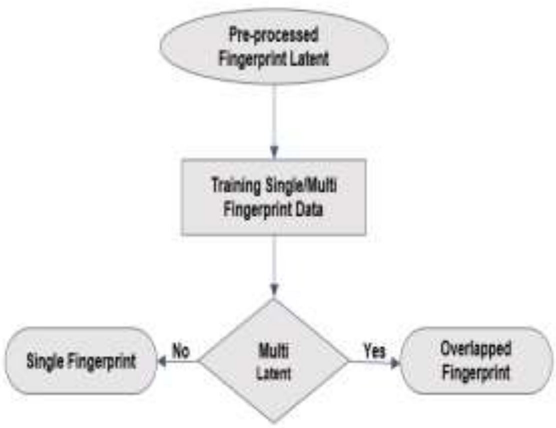

Fig. 3. Latent Fingerprint Classifier Module

The preprocessed image is then fed to Latent Fingerprint Classifier Module. In this module as shown in Fig. 3, it will be trained single/multiple fingerprints. Further DNCNN model classifies from multi latent as single or overlapped fingerprints.

B. *Overlapped Range Detector*

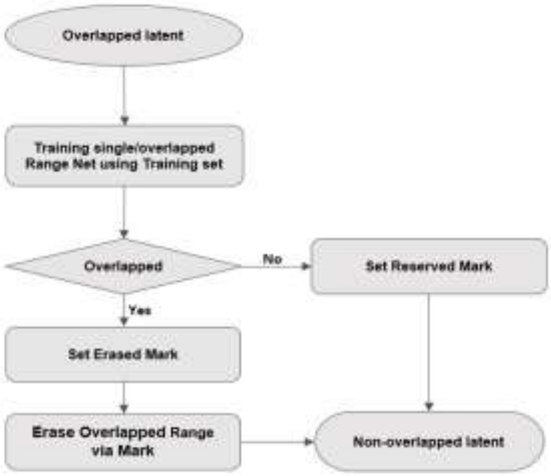

Fig. 4. Overlapped Range Detector Module

In this module as shown in Fig. 4, Overlapped latent image is fed as an input. For each overlapped part it will set reserved and erased mark. For the erased mark it will erase overlapped range. In this way the non-overlapped latent image will be the output.

C. *Fingerprint Reconstructor*

Separated images from Overlapped Range Detector Module is fed as input. Convolutional Autoencoder is used to learn efficient representations from the separated images, and then recover the data from these encoded representations. From this Reconstructor module we obtain reconstructed images.

IV. IMPLEMENTATION

A. *Dataset*

- The database is taken from “The Tsinghua Latent Overlapped Fingerprint Database” [13].
- The Tsinghua Latent Overlapped Fingerprint Database contains latent overlapped fingerprints, which were created by pressing two fingers onto paper at the same location and scanning the resulting image using an electronic scanner, such as an HP scanner. The use of a paper-based method to obtain the overlapped fingerprints provides a simple and cost-effective way to generate a large number of overlapping fingerprints for testing and evaluation purposes. The subsequent scanning of the paper-based fingerprints using an electronic scanner provides a digital representation of the overlapped fingerprints that can be used for further analysis and processing.

- This database consists of 12 single fingerprint images and 100 overlapped fingerprint images, which were created by superimposing the single fingerprints.
- Images are in .bmp extension which represents Bitmap Image file.

B. Data Preprocessing

The following preprocessing techniques are performed on the images before giving it as an input image to the deep learning models.

- Denoising Image Datastore: A object to generate batches of denoise image patches.
- Gaussian Noise Standard Deviation: Fraction of the maximum value of the image class.
- Grayscale: The Channel Format specified.

C. Models Used

1. Deep Normalization Convolutional Neural Network (DNCNN): The DNCNN model is a classification system used for overlapped and non-overlapped image classification. This model is referred from papers [6] and [10]. It includes multiple layers that are stacked on top of each other, with each layer comprising a combination of normalization and convolutional operations, followed by a max-pooling layer. The model is trained to identify overlapped region in images based on the features learned by these layers. The architecture of the DNCNN model is illustrated in Fig. 5, where each rectangular block represents a stack of feature maps. The notation used to describe each layer includes the type of layer (NC for normalization and convolutional, P for max-pooling, and FL for fully-connected), the layer number, the filter size, the number of filters, and the dimensions of the feature maps. The DNCNN model replaces traditional convolutional layers with normalization and convolutional layers, enhancing the performance of fingerprint classification and accelerating the training process. DNCNN performs automatic feature extraction and classification, making it valuable for image processing tasks like fingerprint analysis. DNCNN's architecture improves the classification process and makes it an efficient and reliable tool for fingerprint analysis.

The DNCNN architecture comprised a total of 14 layers, including 3 fully-connected layers, 3 pooling layers and 8 normalization and convolution layers. The input data consisted of two sets of 64x64 maps that were augmented by 128-degree rotations. The training set is taken as input to the DNCNN architecture, which modifies the input size, and the input data is then classified by the training network to determine whether it represents a single or overlapped fingerprint. This classification is a crucial step in separating the overlapped fingerprints.

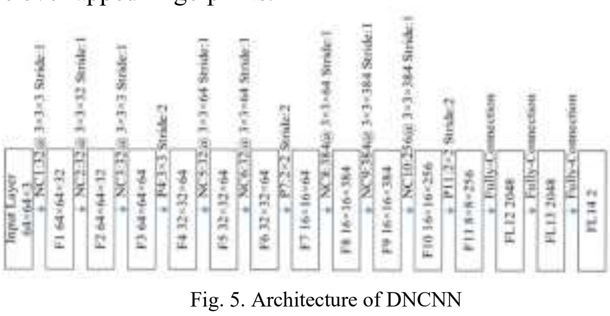

Fig. 5. Architecture of DNCNN

2. Convolutional Autoencoder: The convolutional autoencoder is being used for reconstructing separated fingerprint images [14]. The input images must have dimensions of 224x224x1. To prepare the data for input, the image matrix is first converted into an array, which is then re-scaled and re-shaped to fit within the dimensions of 224x224x1 while maintaining values between 0 and 1. During training, a batch size of 128 is used, which affects the learning parameters and ultimately impacts the prediction accuracy. The autoencoder is comprised of two parts: an encoder and a decoder.

Encoder: The encoder section of the convolutional autoencoder comprises of three layers. The first layer consists of 32 filters that are 3x3 in size, followed by a down sampling (maxpooling) layer. The second layer is made up of 64 filters with the same size of 3x3, and it is also followed by another down sampling layer. The final layer in the encoder contains 128 filters that are 3x3 in size.

Decoder: The decoder section of the convolutional autoencoder also contains three layers. The first layer includes 128 filters with a size of 3x3, followed by an up sampling layer. The second layer consists of 64 filters that are 3x3 in size, and it is followed by another up sampling layer. The final layer of the decoder has one filter that is 3x3 in size.

In convolution auto-encoder there are total 10 layers as shown in the Table. I, in which 6 are convoluted layers,2 are max-pooling layers and other 2 are up sampling layers.

TABLE I. CONVOLUTIONAL AUTOENCODER SUMMARY

Layer (type)	Output Shape	parma#
input_2 (Input Layer)	[(None, 244, 244, 1)]	0
conv2d_6 (Conv2D)	(None, 224, 224, 32)	320
max_pooling2d_2 (MaxPooling2D)	(None, 112, 112, 32)	0
conv2d_7 (Conv2D)	(None, 112, 112, 64)	18496
max_pooling2d_3 (MaxPooling2D)	(None, 56, 56, 64)	0
conv2d_8 (Conv2D)	(None, 56, 56, 128)	73856
conv2d_9 (Conv2D)	(None, 56, 56, 128)	147584
up_sampling2d_2 (UpSampling2D)	(None, 112, 112, 128)	0
conv2d 10 (Conv2D)	(None, 112, 112, 64)	73792
up_sampling2d_3 (UpSampling2D)	(None, 224, 224, 64)	0
conv2d 11 (Conv2D)	(None, 224, 224, 1)	577

- Total params: 314,625
- Trainable params: 314,625
- Non-Trainable params: 0

V. RESULTS

The graph obtained for loss vs epoch using DNCNN model is shown in Fig. 6. The orange line depicts training loss and the blue line depicts training accuracy for 20 epochs. From the Fig. 6, we can infer that the model is not overfit and is suitable for classification of fingerprint images.

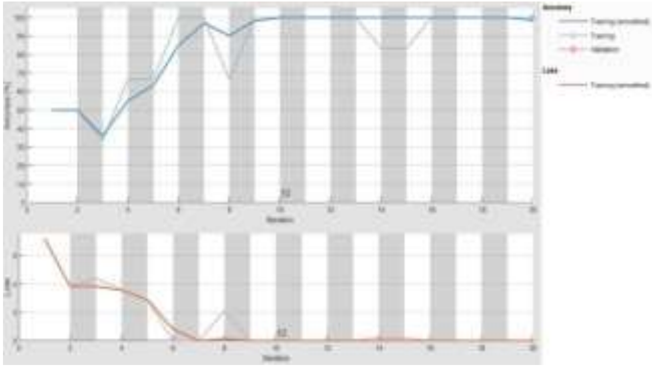

Fig. 6. Accuracy vs Epoch graph of DNCNN

We evaluated the performance of DNCNN model using a test set of 100 instances. Test data consists of 40 non-overlapped fingerprint images(class 1) and 60 overlapped fingerprint images(class 2). Among 40 instances , 34 were correctly classified as class 1, and out of 60 instances, 54 were correctly classified as class 2. The classification report for same is as shown in Table. II where each class's Precision, Recall, F1 score, Macro Avg, Weighted average and support values are depicted.

TABLE II. CLASSIFICATION REPORT

	Precision	**Recall**	**F1 score**	**support**
class 1	0.85	0.85	0.85	40
class 2	0.90	0.90	0.90	60
accuracy			0.88	100
macro avg	0.88	0.88	0.88	100
weighted avg	0.88	0.88	0.88	100

Table. III shows the performance metrics with their scores. We can infer that the Precision is 85.00% indicating that, out of all instances classified as positive, 85.00% were truly positive. The Recall of the model is 85.00%, indicating that out of all truly positive instances, 85.00% were correctly classified as positive by the model. Finally, the F1 score of the model is 85.00%, which is a harmonic mean of precision and recall, indicating that the model achieved a balance between precision and recall. The overall accuracy of the model was 88.00%, which indicates that it correctly classified 88 out of 100 instances.

We also evaluated the performance of DNCNN model using a ROC curve analysis. The ROC curve is a graphical representation of the relationship between the False Positive Rate (FPR) and True Positive Rate (TPR) at different classification thresholds. The Area Under the ROC Curve (AUC) is a widely used metric for evaluating the performance of a classification model, as it provides a measure of the model's ability to distinguish between positive and negative instances. The DNCNN classifier, which corresponds to a diagonal line in the ROC space, achieved an AUC of 0.88, indicating that DNCNN model has excellent classification performance. The ROC curve of DNCNN model is shown in Fig. 7.

TABLE III. PERFORMANCE METRIC

Metric	**Score**
Precision	85.00%
Recall	85.00%
F1 Score	85.00%
Accuracy	88.00%

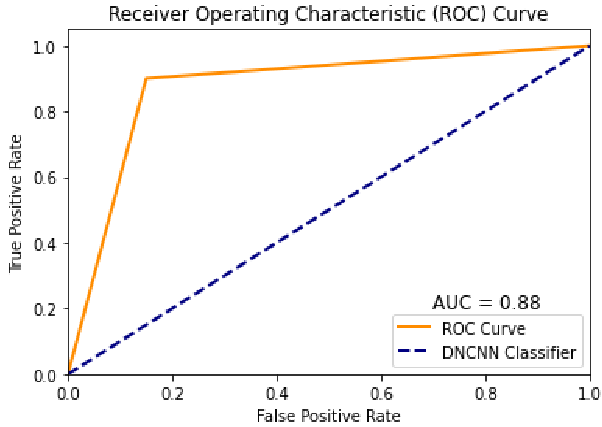

Fig. 7. ROC Curve of DNCNN model

The Regionprops technique of MATLAB was utilized in the proposed work to measure various image quantities and features of a Gray-scaled image. Specifically, by analysing a sample image, this technique automatically identified and determined the properties of each connected region. We have employed this technique for separation of overlapped fingerprints. The results of the separated overlapped fingerprints defined as “Test Images” is as shown in Fig. 9.

From the Fig. 8, we can infer that training loss and validation loss are in same phase which shows that the model is not over-fitting. As epochs are increasing the validation loss is decreasing. Therefore, we can say the Convolutional autoencoder model is good for reconstruction of fingerprint images. The results of the reconstructed fingerprint images from Convolutional Autoencoder is as shown in Fig. 9. The resulting images are much more efficient.

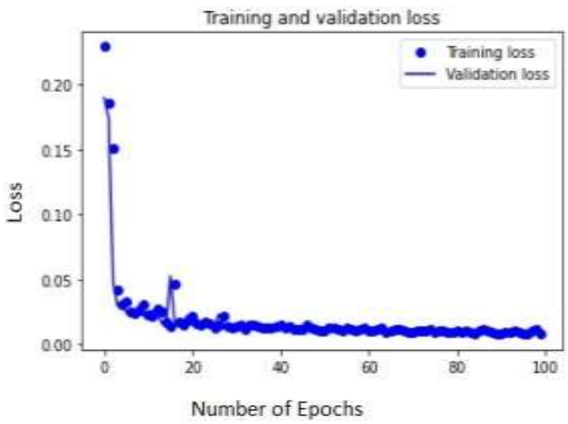

Fig. 8. Training and Validation Loss vs Epoch graph of Convolutional Autoencoder

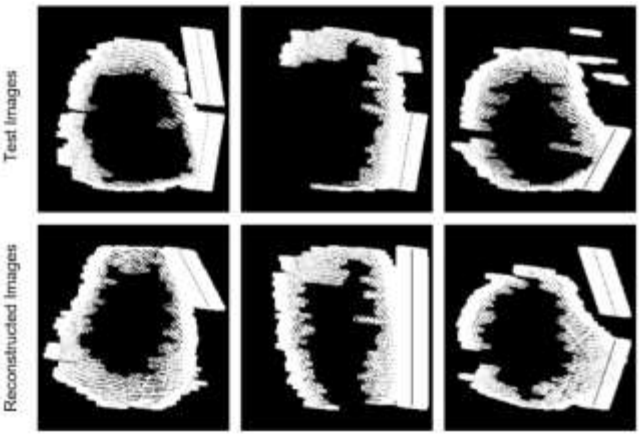

Fig.9. Samples of the reconstructed images by using Convolutional Autoencoder

TABLE IV. PERFORMANCE METRIC

DNCNN Model	Accuracy
Chi-Hsiao Yih et.al	92.39%
Proposed work using Train data	100.00%
Proposed work using Test data	88.00%

The performance comparison between the proposed work and a similar study conducted by the author in \cite{b6} is presented in Table. IV. We can observe that the proposed system efficiently classifies overlapped and non-overlapped fingerprints. Further the non-overlapped fingerprints are reconstructed using Convolutional Autoencoder. Further the non-overlapped fingerprints are reconstructed using Convolutional Autoencoder with an accuracy of 65.2%.

VI. CONCLUSION

Every human being has certain physical marks which do not change and could be a possible way of identifying him/her. Fingerprints are a permanent and unique mark, making them an ideal biometric unit for human identification. Overlapped fingerprints often used at crime scenes are unsuitable for investigation. Separating the overlapped fingerprints is a challenging task. The proposed work utilized the Tsinghua simulated overlapped fingerprint image database to train the DNCNN model, which achieved a classification accuracy of 100% on trained data and 88% on test data for distinguishing between overlapped and non-overlapped fingerprints. The overlapped fingerprints are further separated using Regionprops technique available in MATLAB. These separated images are reconstructed using Convolutional Autoencoder with an accuracy of 65.2%. The proposed work can be extended by experimenting with different image reconstruction techniques and using a large amount of dataset having high-quality standard fingerprint images.

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