JOIV : Int. J. Inform. Visualization, 8(3-2): IT for Global Goals: Building a Sustainable Tomorrow - November 2024 1635-1642

INTERNATIONAL JOURNAL
ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

An Automated Fingerprint Image Detection and Localization Approach-based Unsupervised Learning Algorithms using Low-quality Biometrics Plam Data

Abdulrasool Jadaan Abed [a,*], Dhahir Abdulhadi Abdullah [a]

[a] *Department of Computer Science, College of Sciences, University of Diyala, Iraq*
Corresponding author: [*]scicompms222315@uodiyala.edu.iq

***Abstract*—In this study, fingerprint identification and classification of low-quality fingerprints have been analyzed accordingly. As technology advances and methodologies evolve, staying at the forefront of research and innovation is imperative. The challenges addressed in this paper provide a foundation for future investigations and underscore the importance of developing resilient and adaptable biometric systems for real-world applications. The quest for accurate, efficient, and robust fingerprint identification in adverse conditions is a testament to the continuous evolution and refinement of machine learning and deep learning approaches in biometrics. While deep learning models exhibited improved performance, it is essential to acknowledge the need for further research and development in this domain. Additionally, integrating multimodal biometric systems and combining fingerprint data with other biometric modalities might present a viable avenue for mitigating the limitations associated with degraded fingerprints. In this paper, we develop a fingerprint identification approach for low-quality fingerprint images. The success rate accuracy of the propped algorithm for the low-quality fingerprint images should be significantly better than that of the standard local minutia approach. The main design of our deep learning approach is based on detecting and extracting the primary correlation during the training and using the correlation feature map to calculate the distance between the low-quality fingerprint images during the predicting phase. The experimental results show a very promising repulsing and high prediction accuracy.**

***Keywords*—Fingerprint; low quality; deformed fingerprint; deep learning.**

Manuscript received 7 Apr. 2024; revised 19 Jun. 2024; accepted 17 Aug. 2024. Date of publication 30 Nov. 2024.

I. INTRODUCTION

Reliable personal information is essential for person identification methods that aim to identify or verify the identity of individuals using various systems. Participants and users requesting services from the system in question rightfully place a high value on this information in some instances [1]. The system's main goal is to ensure that only authorized users can access the provided services, including person identification and verification tasks [2]. The systems are excellent examples: Asynchronous Teller Machines (ATMs), personal laptops, cellular phones, bank accounts, and protected building access. However, imposters can easily pull off their schemes without a solid authentication system that includes (identification and verification) procedures [3]. In biometrics, fingerprints are the most crucial component of human identity. From birth to death, they remain distinct.

As a result, fingerprints are valuable in forensics and identity verification. Since the quality of the fingerprint information depends on the quality of the scanned fingerprint picture, accurately and reliably classifying low-quality fingerprints is a challenging data recognition/classification operation. Because recognition success depends on the feature extraction and matching stage, fingerprint recognition systems are susceptible to picture noise and degradation levels. It is often preferred to remove low-quality fingerprint images and replace them with acceptable high-quality ones when using Fingerprint Identification Systems (FIS), which include fingerprint identification approaches because these systems rely on the quality of the fingerprint images.

Acquiring device circumstances (such as dirtiness, sensor, and time) and individual artifacts (such as skin environment, age, skin illness, and pressure) are among the many elements that impact the fingerprint picture quality. Partial fingerprint image degradation can occur due to many of these circumstances. Clear ridges and valleys, and hence the "extractability" of the identification characteristics, are often what determine the quality of fingerprint photographs [4] [5]. For the identification and verification work, poor-quality fingerprint processing is necessary for improved performance accuracy instead of trying to improve the input picture during pre-processing. This paper aims to use deep learning approaches to study and enhance low-quality fingerprint recognition and categorization.

Traditional identification methods are sometimes hampered by defective fingerprint pictures, which include noise, distortions, and variances; this research aims to overcome these issues. The ultimate goal is to create efficient and trustworthy methods that can accurately use fingerprints to identify and categorize people, even when the data quality is poor. A method for identifying fingerprints from low-quality photos was suggested in this research. The propped algorithm outperforms the conventional local minutia technique regarding success rate accuracy when used in low-quality fingerprint photos. Examining the performance of the proposed system is essential for identifying its behavior when evaluated on low-quality fingerprint photos. Additionally, we will examine how this behavior is affected by the loss of partial fingerprint information [6] [7]. Some relevant papers on low-quality fingerprint identification and recognition are summarized here.

According to the authors of [8] [9], he has been working on improving fingerprint identification under challenging environments, such as those with low-quality fingerprints that are distorted and noisy. The authors suggest an architecture for a deep convolutional neural network (CNN) that can automatically learn discriminative features from fingerprint photos that have been damaged, leading to more accurate and resilient results. This extensive review examines several fingerprint identification systems, highlighting the difficulties and potential solutions for handling low-quality fingerprint data [10]. It delves into the shortcomings of conventional approaches, and the improvements ML and DL methods offer to meet these problems.

This study presents an adaptive learning framework developed for low-quality fingerprint recognition. Improved adaptation to fluctuations in picture quality and resilient performance in demanding settings are achieved by the suggested system, which dynamically adapts its learning parameters based on the quality of input fingerprint data. In their study of uncontrolled settings, [11] propose a two-pronged fingerprint enhancement and recognition strategy. The goal of the improvement step is to improve low-quality fingerprint photos, and then we'll use sophisticated machine-learning techniques to identify them. The research shows that accuracy is improved in difficult circumstances. In this study, [12] investigate techniques for low-quality fingerprint detection that rely on sparse representations. The suggested solution shows promise when conventional approaches fail by using fingerprint characteristics' sparsity to manage input data distortions and noise.

This study utilizes deep transfer learning algorithms and focuses on the cross-sensor scenario when fingerprint pictures are obtained from several sensors with variable characteristics [13]. Improved identification performance is achieved by adapting the model to accommodate low-quality fingerprints from various sensors by drawing on knowledge from a high-quality dataset. Kumar, A., et al. In this study, we provide a hybrid method for low-quality fingerprint identification that combines ensemble learning with local binary patterns (LBP). LBP features generate local fingerprint patterns from damaged images, and ensemble learning approaches are used for robust classification to increase performance in difficult situations. [15]. This study offers a privacy-preserving method for matching low-quality fingerprint photos and focuses on privacy issues related to fingerprint identification. This study delves into cryptographic methods for fingerprint template security, intending to protect user privacy without sacrificing identification accuracy in low-quality data environments.

II. Materials and Method

A. Preprocessing Stage: Low-Quality Biometrics Data Preprocessing

The first stage of our proposed system is designed to preprocess low-quality biometric data. Different image processing tools are designed and implemented in this stage, such as image transformation, image binarization, and image postprocessing. The first step of the preprocessing processing stage is image transformation. In this step, image transformation, normalization, and intensity adjustment are applied to each biometric image [16], [17].

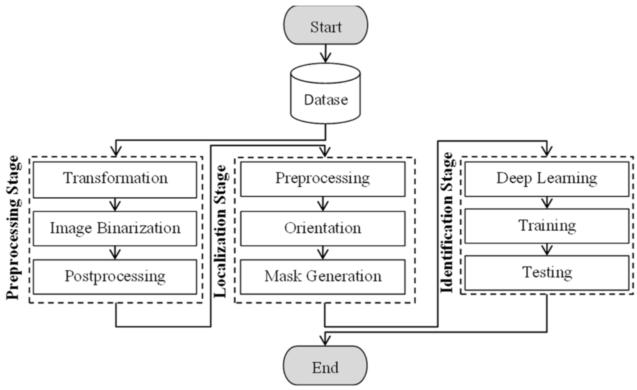

Fig. 1 Low-Quality Fingerprint Localization Based Low-Quality Biometrics Data

During the image transformation, each biometric image is converted to a grayscale image using the "rgb2gray()" function, as is shown in Fig.2 (b). Converting low-quality biometric photos to binary images is the second phase of the first stage, which is creation and implementation. A worldwide cutoff is established. The luminosity of the picture dictates the threshold value. It will be set to zero if each pixel is less than the threshold; otherwise, it will remain untouched. As can be seen in Figure 2 (c), the biometric picture underwent image binarization using a global thresholding approach [19].

B. Fingerprint Alignment Step

The alignment of fingerprints is the last stage in the fingerprint detection and localization process. This stage involves isolating each fingerprint object before aligning the extracted binary mask among the x-axes. This is done after each fingerprint object has been localized using the perfect binary mask for each binary fingerprint. Once the binary fingerprint mask is aligned correctly, the initial, low-quality fingerprint picture is also adequately aligned [20], [21].

First, we isolate each fingerprint item using the perfect binary mask for localization. Then, we align the extracted binary mask among the x-axes. We begin by extracting the total number of binary objects from the morphological operations using the "regionprops()" function. In Fig.2 (j), the blue box shows the results of utilizing the "measurements.BoundingBox" method to extract some features of binary objects, such as the object center and the finger bounding box. From there, a perfect binary mask "square" is created using "polyshape" and superimposed over the retrieved one, as seen in Figure 2.

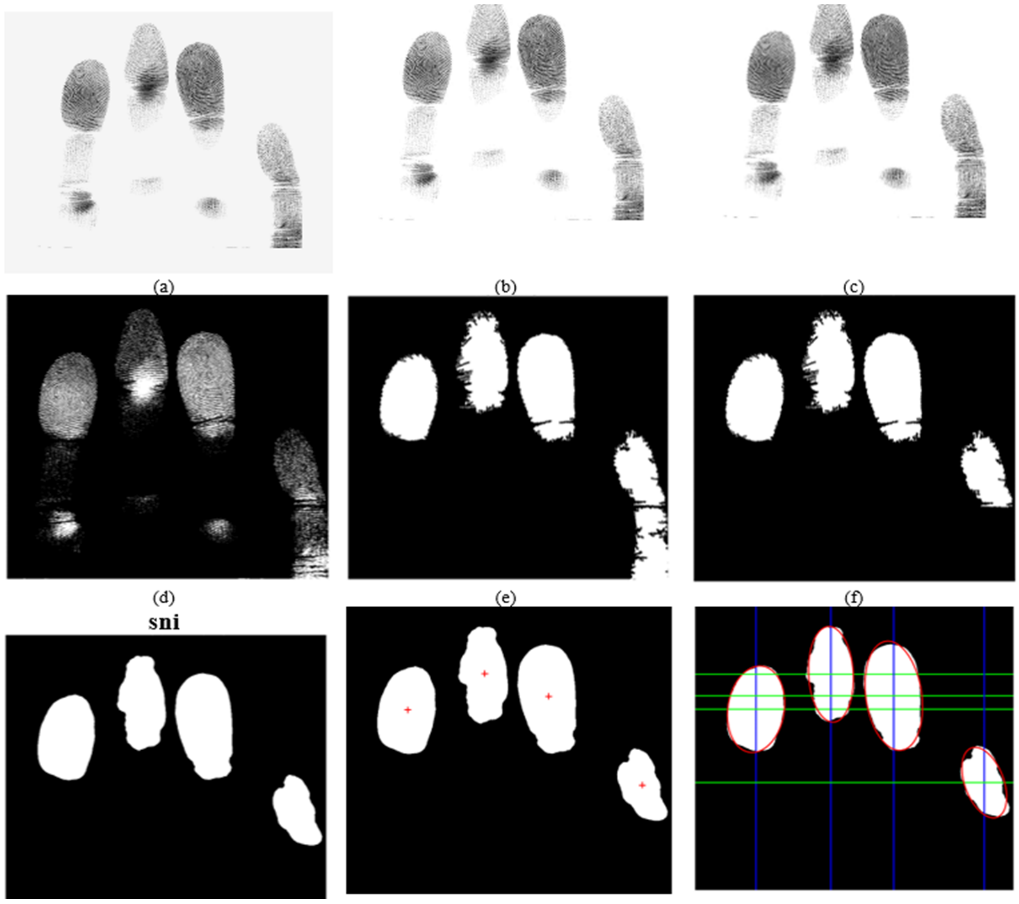

Fig. 2 Biometric data pre-processing result.

III. Results and Discussion

A. Low-quality Fingerprint Dataset

The dataset that is used in our proposed system is the SD-302b [22], [23]. It consists of the operator-assisted rolled fingerprint impressions used as a baseline to quantify Challenger performance and 4-4-2 slap impressions used to ensure the veracity of the reported rolled friction ridge generalized positions. The images are distributed in the Portable Network Graphics (PNG) image format. Please refer to NIST Technical Note 2007 [24] for complete details. For details about the N2N Fingerprint Challenge, please refer to NIST Interagency Report 8210 [25]. The first dataset information is illustrated in the following Table 1.

TABLE I
Low-quality fingerprint dataset description (SD-302b)

Dataset Name	Device type	Resolution	Image format	No. of images
Sd302b	plain	500	*.png	276

For SD 302b, baseline data is distributed as PNG files. For those devices that captured at a resolution other than 196.85 pixels per centimeter (PPCM) (500 pixels per inch, or PPI), images resampled at 196.85 PPCM (500 PPI) are available. Samples are from the 302b dataset.

B. Evaluation Criteria

Our proposed system's low-quality fingerprint detection, localization, and identification evaluation performance is based on two evaluation metrics. The proposed system produces different versions from the same dataset. For instance, the first approach, "low-quality fingerprint detection and localization approach," produces three datasets. The first one is the original SD 302b after detection and localized each fingerprint, while the second dataset is the aligned SD 302b dataset, and the third one is the localized SD 302b[26] dataset. Each dataset is used as a training/testing dataset for the third approach, "low-quality fingerprint identification and classification approach". For this task, different criteria such as Accuracy, precision, Recall, and F1-measure and are used to evaluate our first approach

C. Low Quality Fingerprint Detection and Isolation Experimental Results

Our approach's experimental result is based on using all biometric images from the SD-302b dataset. In this stage, our proposed method uses two biometric images from the SD-302b dataset to detect and localize each class (individual) fingerprint image. The dataset is pre-processed by splitting it into multiple classes based on the dataset configuration. Samples from the dataset are illustrated in Table 2.

TABLE II
LOW QUALITY FINGERPRINT DETECTION AND PREPARATION EXPERIMENTAL RESULTS USING SD-302B LOW-QUALITY FINGERPRINT DATASET

No. of Classes	No. of Images per Class	Image format	Total No. of images
92	10	*.png	920

As shown in Fig.4, each of the three biometric images from the SD-302b produces 10 individual low-quality fingerprint images. These are collected and isolated automatically through our first approach in one individual class, for a total of 92 classes. Each class has ten individual low-quality fingerprint images [27], [28].

D. Low Quality Fingerprint Aligning and Localization Experimental Results

The second experimental result of our first approach is based on producing different versions of the first dataset that are automatically generated through our first approach. Each fingerprint automatically detected in this stage is aligned and localized [29], [30].

Fig. 4 Sample images from the detection and preparation of experimental results using the SD-302b Low-quality fingerprint dataset.

TABLE III
LOW-QUALITY FINGERPRINT DETECTION, ALIGNING, AND LOCALIZATION EXPERIMENTAL RESULTS USING SD-302B LOW-QUALITY FINGERPRINT DATASET.

Generated Dataset	Total No. of Classes	Images Per Class	Image format	Total No. of images
Original	92	10	*.png	920
Aligned	92	10	*.png	920
Localized	92	10	*.png	920

This generates three different datasets (original, aligned, and localized) with a total of 2760 low-quality fingerprint images. Table 3 illustrates the total number of images for each dataset, and some samples from different datasets are also included.

E. Low-quality Fingerprint Image Aligning Experiential Results

The first part of this experimental result is the low-quality fingerprint image alignment. In this part, each individual low-quality fingerprint image is automatically aligned using our first approach, "low-quality fingerprint image aligning and localization approach." Samples from the aligned low-quality fingerprint dataset are shown in Fig.5.

Fig. 5 Sample images from low-quality fingerprint aligning experimental results using SD-302b Low-quality fingerprint dataset.

F. Low-quality Fingerprint Image Localization Experiential Results

The second part of this experimental result is the low-quality fingerprint image localization. In this part, each low-quality fingerprint image is automatically localized, and the ROI of each fingerprint is automatically extracted and localized using our first approach, "low-quality fingerprint image aligning and localization approach". Samples from localized low-quality fingerprint datasets. The proposed deep learning approach implemented in our third approach for low-quality fingerprint identification and classification has been used to identify and classify low-quality fingerprints. The main task of this approach is to find the main correlation between the low-quality fingerprints through the training phase. Then, the learning parameters (learned correlation map) are used later to predict the correct label for the low-quality fingerprint in the testing dataset. Each dataset (original, aligned, and localized) is split into training and testing datasets using 70% training and 30% testing. Table 4 below describes the training testing scheme for the third proposed approach.

TABLE IV
SHOW THE DATA PARTITIONS OF OUR PROPOSED SYSTEM USING SD-302B LOW-QUALITY FINGERPRINT DATASET

Data Partition	Number of images
Training and Validation 70%	644
Testing 30%	276
Total	920

This approach trains our proposed deep learning model on three different datasets, as shown in Table 5 below.

TABLE V
THE WHOLE DATASET THAT HAS BEEN USED IN THE PROPOSED LOW-QUALITY FINGERPRINT IDENTIFICATION AND CLASSIFICATION APPROACH USING THE SD-302B DATASET

Dataset	**Data Partition**	**Number of images**
Original low-quality fingerprints dataset	Training-Validation 70%	644
	Testing 30%	276
	Total	920
Aligned low-quality fingerprint dataset	Training-Validation 70%	644
	Testing 30%	276
	Total	920
Localized low-quality fingerprint dataset	Training-Validation 70%	644
	Testing 20%	276
	Total	920
Total		2760

G. *Experimental Results using the Original SD-302b Low-quality Fingerprint Dataset*

The first dataset used is the original detected low-quality fingerprint dataset. The training and testing scheme used in this experimental result, such as the training parameters and number of epochs, learning rate, and the accuracy of the first experiment, are explained in Table 6. To come up with the best training/testing parameters, we tried different learning methods (parameters). The best learning parameters with the highest accuracy were using 400 epochs, with 64 learning patches and 4400 iterations per epoch. For this reason, we used these parameters as our final learning platform for other experimental results.

TABLE VI
TRAINING SCHEME AND PARAMETERS FOR THE FIRST APPROACH USING THE ORIGINAL SD-302B LOW-QUALITY FINGERPRINT DATASET

No. of Epochs	Batch Size	Training Time	No. of Iteration	Iteration Epoch	Learning Rate	Accuracy
50	16	15 min	2000	40	0.0001	83.54%
100	16	31 min	4000	40	0.0001	87.42%
	32	18 min	2200	11	0.0001	91.30%
200	64	15 min	1100	8	0.0001	91.89%
	128	13 min	200	5	0.0001	92.39%
	32	71 min	9200	23	0.0001	92.12%
400	64	33 min	4400	11	0.0001	93.34%
	128	24 min	2000	5	0.0001	93.07%

As discussed above, the training loss and the validation accuracy for the low-quality fingerprint identification and classification were based on using 200 epochs only, with 128 learning patch and 200 iterations per epoch. The confusion metrics of the testing dataset is also shown in the following Fig. 6 (a) and (b) respectively. Some testing samples of the low-quality fingerprint identification and classification based on using 200 epochs only, with 128 learning patch and 200 iterations per epochs is shown below in the following Fig.7

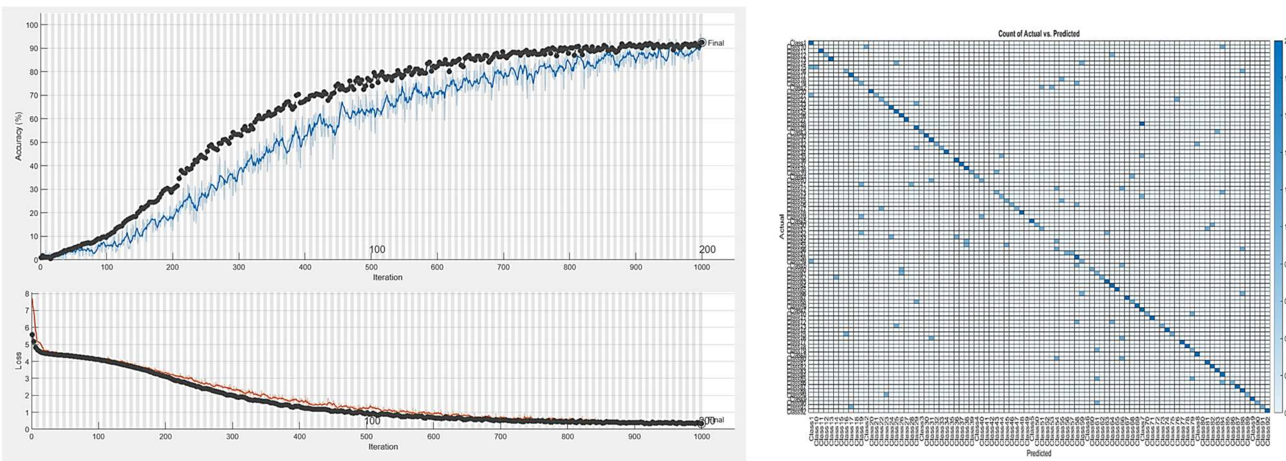

Fig. 6 (a) Training loss and validation accuracy for the low-quality fingerprint identification and classification approach using SD-302b Low-quality fingerprint dataset using 200 epochs, 64 learning patches and 1100 iterations, (b) Confusion metrics for the testing dataset for the low-quality fingerprint identification and classification approach using SD-302b Low-quality fingerprint dataset using 200 epochs, 64 learning patches and 1100 iterations

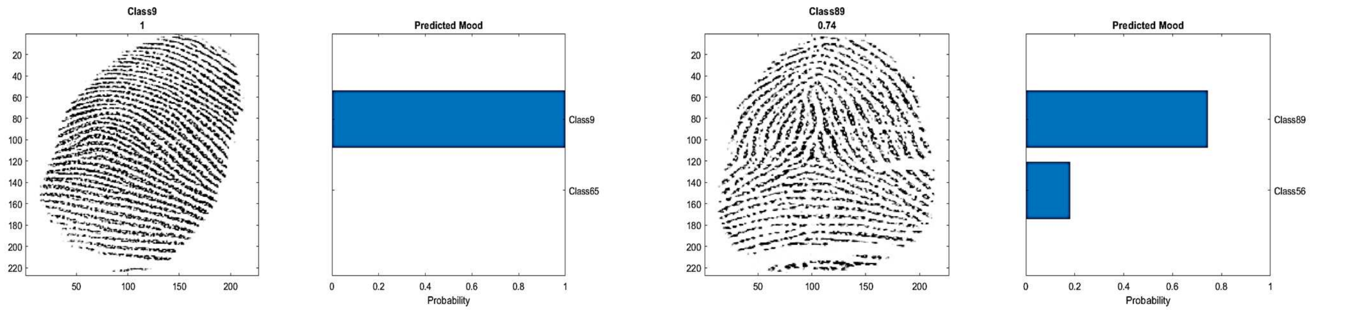

Fig. 7 Testing samples of the low-quality fingerprint identification and classification approach using SD-302b Low-quality fingerprint dataset using 200 epochs, 128 learning patches, and 200 iterations.

H. *Experimental Results using the Aligned SD-302b Low-quality Fingerprint Dataset*

The second dataset used is the aligned low-quality fingerprint dataset. The training and testing scheme used in this experimental result is Table 7, which explains the training parameters, number of epochs, learning rate, and accuracy of the first experimental experiment. As discussed above, the training loss and the validation accuracy of using 400 epochs only, with 64 learning patches and 4800 iterations per epoch are shown below in the following Fig. 7. The confusion metrics of the testing dataset are also shown in the following Fig.8. Some testing samples of the low-quality fingerprint identification and classification based on using aligned SD-302b Low-quality fingerprint dataset is shown below in the following Fig. 9.

TABLE VII
TRAINING SCHEME AND PARAMETERS FOR THE FIRST APPROACH USING THE ALIGNED SD-302B LOW-QUALITY FINGERPRINT DATASET.

No. of Epochs	Batch Size	Training Time	No. of Iteration	Iteration Epoch	Learning Rate	Accuracy
400	64	38 min	4800	12	0.0001	95.65%

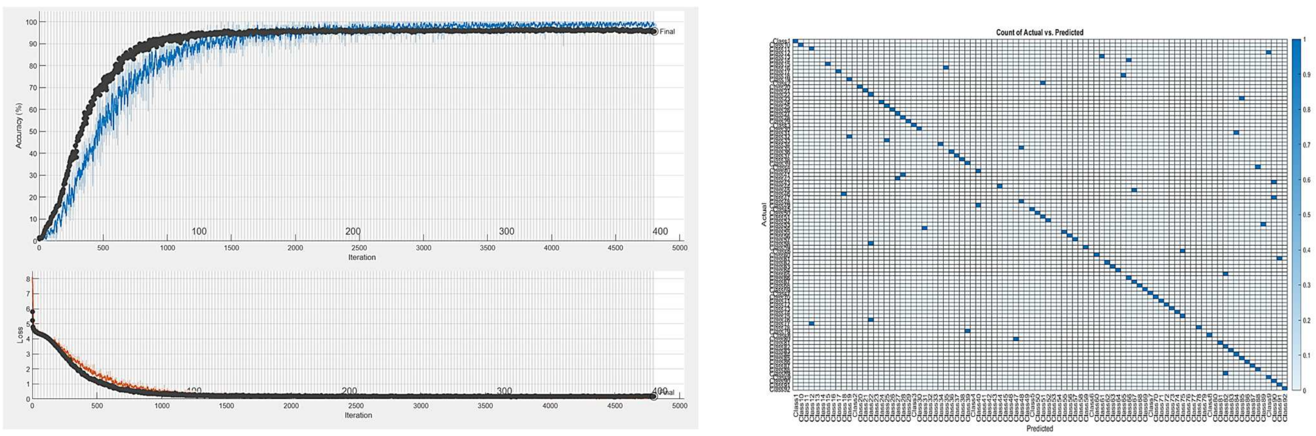

Fig. 8 (a) Training loss and validation accuracy for the low-quality fingerprint identification and classification approach using aligned SD-302b Low-quality fingerprint dataset with 400 epochs, 64 learning patches and 4800 iterations, (b) Confusion metrics for the testing dataset for the low-quality fingerprint identification and classification approach using SD-302b Low-quality fingerprint dataset using 50 epochs, 16 learning patches and 2000 iterations per epoch.

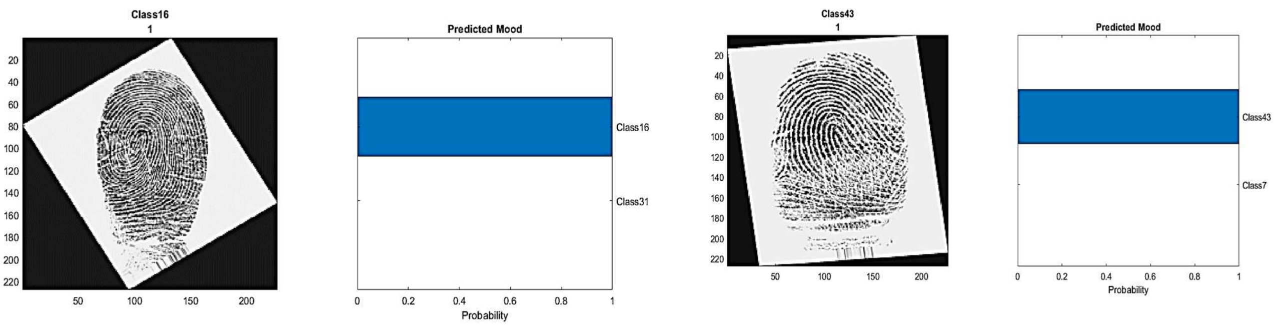

Fig. 9 Testing samples of the low-quality fingerprint identification and classification approach using aligned SD-302b Low-quality fingerprint dataset using 400 epochs, 64 learning patches, and 4800 iterations.

I. *Experimental Results using the Localized SD-302b Low-quality Fingerprint Dataset*

The third dataset used is the aligned low-quality fingerprint dataset. Table 8 explains the training and testing scheme used in this experimental result, including the training parameters, number of epochs, learning rate, and accuracy of the first experiment.

TABLE VIII
TRAINING SCHEME AND PARAMETERS FOR THE FIRST APPROACH USING THE LOCALIZED SD-302B LOW-QUALITY FINGERPRINT DATASET.

No. of Epochs	Batch Size	Training Time	No. of Iteration	Iteration Epoch	Learning Rate	Accuracy
400	64	37 min	4800	12	0.0001	97.10%

As discussed above, the training loss and the validation accuracy of using 400 epochs only, with 64 learning patches and 4800 iterations per epoch is shown below in the following Fig.10. The confusion metrics of the testing dataset are also shown in the following Fig.11. Some testing samples of the low-quality fingerprint identification and classification based on using aligned SD-302b Low-quality fingerprint dataset is shown below in the following Fig.11.

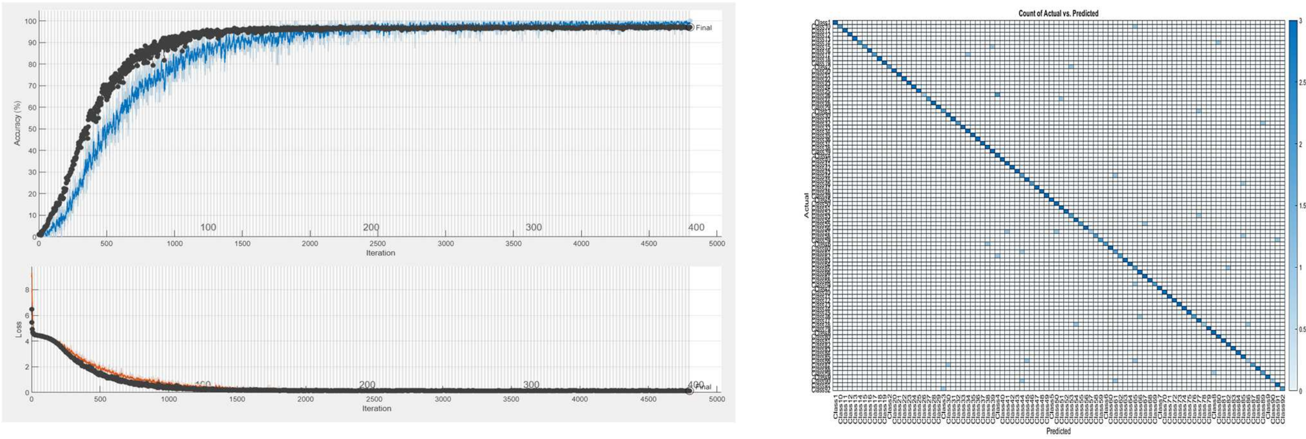

Fig. 10 (a) Training loss and validation accuracy for the low-quality fingerprint identification and classification approach using localized SD-302b Low-quality fingerprint dataset with 400 epochs, 64 learning patches and 4800 iterations, (b) Confusion metrics for the testing dataset for the low-quality fingerprint identification and classification approach using localized SD-302b Low-quality fingerprint dataset using 50 epochs, 16 learning patches and 2000 iterations per epoch

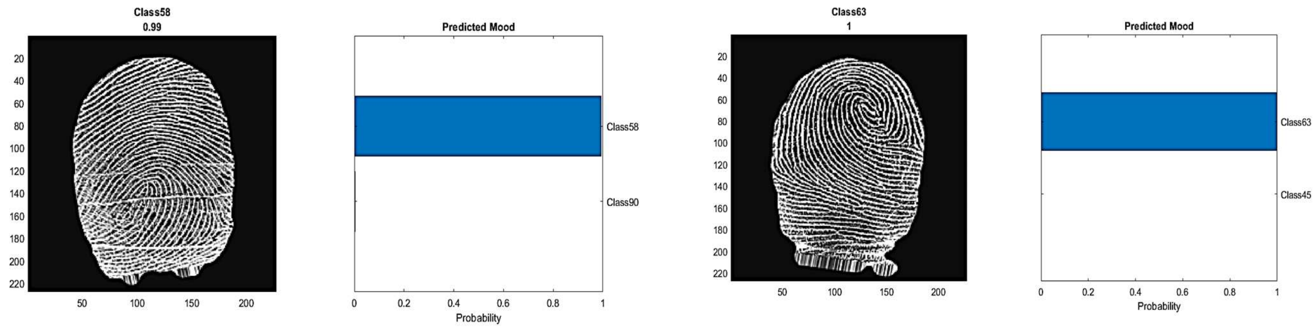

Fig. 11 Testing samples of the low-quality fingerprint identification and classification approach using aligned SD-302b Low-quality fingerprint dataset using 400 epochs, 64 learning patches and 4800 iterations.

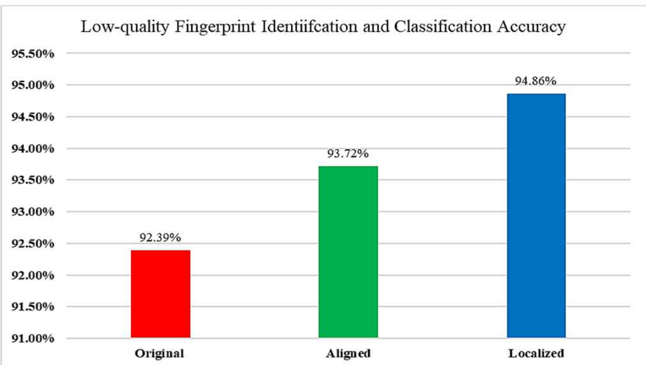

Fig. 12 Overall testing performance of the low-quality fingerprint identification and classification approach using original, aligned, and localized SD-302b Low-quality fingerprint dataset.

In general, Fig. 12 illustrates the overall performance of the low-quality fingerprint identification and classification approach using different datasets of the SD-302b low-quality fingerprint, such as the original detected one, aligned one, and localized one.

IV. CONCLUSION

In conclusion, pursuing effective low-quality fingerprint identification and classification using machine learning and deep learning approaches has been challenging yet critical. This thesis has delved into the issue of low-quality fingerprint data and its impact on the accuracy of identification and classification systems. The findings and insights gained throughout this research shed light on the complexities and limitations of leveraging these advanced techniques in scenarios where fingerprint quality is compromised. Exploring traditional machine learning methods revealed that their performance is significantly hindered when confronted with low-quality fingerprint images. The sensitivity to noise, distortions, and variations in such data proved a major obstacle in achieving reliable identification and classification outcomes. Despite incorporating feature engineering and extraction techniques, these methods exhibited limitations in handling the intricacies of degraded fingerprint images. Integrating deep learning approaches, particularly convolutional neural networks (CNNs), showcased promise in addressing some of the challenges posed by low-quality fingerprints. CNN demonstrated an inherent ability to learn hierarchical representations directly from raw input data, enabling them to capture complex patterns and features even in noise and distortions. However, the effectiveness of deep learning models is contingent upon the availability of large and diverse training datasets, which may be scarce for low-quality fingerprint scenarios

REFERENCES

[1] W. Li, J. You, and D. Zhang, "Texture-based palmprint retrieval using a layered search scheme for personal identification," IEEE Transactions on Multimedia, vol. 7, no. 5, pp. 891–898, Oct. 2005, doi:10.1109/tmm.2005.854380.

[2] A. K. Jain, R. Bolle, and S. Pankanti, Biometrics: Personal Identification in Networked Society. Norwell, MA, USA: Kluwer, 1999.

[3] M. Ye, J. Shen, G. Lin, T. Xiang, L. Shao, and S. C. H. Hoi, "Deep Learning for Person Re-Identification: A Survey and Outlook," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 6, pp. 2872–2893, Jun. 2022, doi: 10.1109/tpami.2021.3054775.

[4] M. A. Ferrag, L. Maglaras, A. Derhab, and H. Janicke, "Authentication schemes for smart mobile devices: threat models, countermeasures, and open research issues," Telecommunication Systems, vol. 73, no. 2, pp. 317–348, Sep. 2019, doi:10.1007/s11235-019-00612-5.

[5] R. Clarke, "Human Identification in Information Systems," Information Technology & People, vol. 7, no. 4, pp. 6–37, Dec. 1994, doi: 10.1108/09593849410076799.

[6] C. Pope, "Biometric data collection in an unprotected world: Exploring the need for federal legislation protecting biometric data", J. Law Policy, vol. 26, no. 2, pp. 769, 2018.

[7] T. Dunstone and N. Yager, Eds., Biometric System and Data Analysis. Springer US, 2009. doi: 10.1007/978-0-387-77627-9.

[8] R. de Luis-García, C. Alberola-López, O. Aghzout, and J. Ruiz-Alzola, "Biometric identification systems," Signal Processing, vol. 83, no. 12, pp. 2539–2557, Dec. 2003, doi:10.1016/j.sigpro.2003.08.001.

[9] J. Bringer, H. Chabanne, and B. Kindarji, "Identification with encrypted biometric data," Security and Communication Networks, vol. 4, no. 5, pp. 548–562, Apr. 2011, doi: 10.1002/sec.206.

[10] H.-K. Song et al., "Deep user identification model with multiple biometric data," BMC Bioinformatics, vol. 21, no. 1, Jul. 2020, doi:10.1186/s12859-020-03613-3.

[11] M. K. Khan, J. Zhang, and L. Tian, "Protecting Biometric Data for Personal Identification," Advances in Biometric Person Authentication, pp. 629–638, 2004, doi: 10.1007/978-3-540-30548-4_72.

[12] W. Shen and T. Tan, "Automated biometrics-based personal identification," Proceedings of the National Academy of Sciences, vol. 96, no. 20, pp. 11065–11066, Sep. 1999, doi:10.1073/pnas.96.20.11065.

[13] J. Yuan and S. Yu, "Efficient privacy-preserving biometric identification in cloud computing," 2013 Proceedings IEEE INFOCOM, pp. 2652–2660, Apr. 2013, doi:10.1109/infcom.2013.6567073.

[14] A. K. Jain and A. Kumar, "Biometric Recognition: An Overview," Second Generation Biometrics: The Ethical, Legal and Social Context, pp. 49–79, 2012, doi: 10.1007/978-94-007-3892-8_3.

[15] V. Awasthi, V. Awasthi, and K. K. Tiwari, "Finger print analysis using termination and bifurcation minutiae," Int. J. Emerg. Technol. Adv. Eng., vol. 2, pp. 124–130, Feb. 2012.

[16] M. Kaur, M. Singh, A. Girdhar and S. Parvinder, "Fingerprint verification system using minutiae extraction technique", World Academy of Science Engineering and Technology, vol. 46, pp. 497-502, 2008.

[17] N. Rivaldería and E. Gutiérrez-Redomero, "Interpopulational differences in the frequency and distribution of delta types," Forensic Science International, vol. 322, p. 110749, May 2021, doi:10.1016/j.forsciint.2021.110749.

[18] Q. Zhao, D. Zhang, L. Zhang, and N. Luo, "Adaptive fingerprint pore modeling and extraction," Pattern Recognition, vol. 43, no. 8, pp. 2833–2844, Aug. 2010, doi: 10.1016/j.patcog.2010.02.016.

[19] A. K. Jain, Y. Chen, and M. Demirkus, "Pores and Ridges: High-Resolution Fingerprint Matching Using Level 3 Features," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no. 1, pp. 15–27, Jan. 2007, doi: 10.1109/tpami.2007.250596.

[20] P. Tertychnyi, C. Ozcinar, and G. Anbarjafari, "Low-quality fingerprint classification using deep neural network," IET Biometrics, vol. 7, no. 6, pp. 550–556, Oct. 2018, doi: 10.1049/iet-bmt.2018.5074.

[21] S. Kriangkhajorn, K. Horapong, and V. Areekul, "Spectral Filter Predictor for Progressive Latent Fingerprint Restoration," IEEE Access, vol. 12, pp. 66773–66800, 2024, doi:10.1109/access.2024.3397729.

[22] H. Byeon et al., "Artificial intelligence-Enabled deep learning model for multimodal biometric fusion," Multimedia Tools and Applications, vol. 83, no. 33, pp. 80105–80128, Feb. 2024, doi:10.1007/s11042-024-18509-0.

[23] S. K. Gupta, A. Alemran, C. P. Ranjith, and M. S. K. Mohideen, "Reliable Fingerprint Classification Based on Novel Deep Learning Approach," Advancements in Science and Technology for Healthcare, Agriculture, and Environmental Sustainability, pp. 353–360, Apr. 2024, doi: 10.1201/9781032708348-54.

[24] V Kakulapati, S Subhani, D Madireddy, R Mounika and A Bhargavi, "Fingerprint Recognition Using the HoG and Lime Algorithm," Acta Scientific Computer Sciences, vol. 6, no. 6, 2024.

[25] A. Tarek Mahmoud et al., "An Automatic Deep Neural Network Model for Fingerprint Classification," Intelligent Automation & Soft Computing, vol. 36, no. 2, pp. 2007–2023, 2023, doi:10.32604/iasc.2023.031692.

[26] K. Anusha and P. V. Siva Kumar, "Fingerprint Image Enhancement for Crime Detection Using Deep Learning," Proceedings of the International Conference on Cognitive and Intelligent Computing, pp. 257–268, 2023, doi: 10.1007/978-981-19-2358-6_25.

[27] T. S. Kishore and S. M. Kumar, "Efficient anti-scamming strategy for fingerprint identification using novel enhanced patch based deep learning," The 4TH International Conference on Material Science and Applications, vol. 2822, p. 020059, 2023, doi:10.1063/5.0172962.

[28] T. A. Chmielewski & P. R. Kalata, "Biometric Techniques: The Fundamentals of Evaluation". NIST Special Publication SP, pp. 335-342, 2001.

[29] K. Saeed, "Biometrics Principles and Important Concerns," Biometrics and Kansei Engineering, pp. 3–20, 2012, doi:10.1007/978-1-4614-5608-7_1.

[30] N. V. Boulgouris, Konstantinos N. Plataniotis and Evangelia Micheli-Tzanakou, "PersonSpecific Characteristic Feature Selection for Face Recognition", Biometrics: Theory Methods and Applications, pp. 113-141, 2010.