International Journal of Advances in Applied Sciences (IJAAS)
Vol. 14, No. 4, December 2025, pp. 1350~1358
ISSN: 2252-8814, DOI: 10.11591/ijaas.v14.i4.pp1350-1358

Convolutional neural network model for fingerprint-based gender classification using original and degraded images

Risqy Siwi Pradini[1], Wahyu Teja Kusuma[1], Agung Setia Budi[2]
[1]Program of Informatics, Faculty of Science and Technology, Institut Teknologi Sains dan Kesehatan RS. DR. Soepraoen Kesdam V/BRW, Malang, Indonesia
[2]Departement of Informatics Engineering, Faculty of Computer Science, Universitas Brawijaya, Malang, Indonesia

Article Info

Article history:

Received Sep 6, 2025
Revised Oct 29, 2025
Accepted Nov 4, 2025

Keywords:

Combined data training
Convolutional neural networks
Fingerprint analysis
Gender classification
SOCOFing

ABSTRACT

Fingerprint-based gender classification is a crucial component of soft biometrics, providing valuable additional information to narrow the search space in forensic investigations and large-scale identification systems. Although deep learning models, particularly convolutional neural networks (CNNs), have demonstrated significant potential, performance validation is typically performed on high-quality fingerprint images. This creates a gap between laboratory results and real-world applications, where fingerprint evidence is often found in a degraded state, such as smudged, distorted, or partially damaged. This study attempts to bridge this gap by proposing a more realistic training approach. We design a lightweight and computationally efficient CNN and train it on a comprehensive combined dataset. The main contribution of this study lies in the data training strategy, which explicitly combines real and synthetically modified fingerprint images from the Sokoto coventry fingerprint (SOCOFing) dataset into a single, unified training set. Experimental results show that the proposed model achieves very high classification accuracy (97.39%) on a test set that also includes a combination of original and degraded images. This finding not only confirms the effectiveness of diverse data-based training to produce more robust models but also establishes a new benchmark for fingerprint-based gender classification research under conditions more representative of practical scenarios.

Corresponding Author:

Agung Setia Budi
Department of Informatics Engineering, Faculty of Computer Science, Universitas Brawijaya
Jl. Veteran No. 10-11, Malang, East Java 65145, Indonesia
Email: agungsetiabudi@ub.ac.id

1. INTRODUCTION

Biometrics is a field of science that studies the process of identifying and verifying individuals by utilizing unique and difficult-to-imitate physiological and behavioral characteristics [1]. This field is the main foundation in modern identification and security systems [2], because it utilizes unique physiological or behavioral characteristics to verify a person's identity. Initially, biometric systems focused solely on primary identifiers, such as fingerprint or iris patterns, designed to provide a single identification of an individual. However, recent developments have expanded to include soft biometrics, which refer to predictable physical or behavioral attributes, such as gender, age, or ethnicity [3]. Unlike primary identifiers, these traits are not unique to everyone. However, the added value of soft biometrics lies in their ability to provide contextual information that supports the identification process.

In forensic investigations, soft biometrics plays a crucial role [4]. For example, when latent fingerprints are found at a crime scene, additional information such as estimated gender can help narrow down the list of suspects from a large biometric database [5]. This screening process significantly improves the efficiency and speed of investigations, allowing law enforcement officials to focus their resources more effectively. Therefore, developing reliable methods for extracting soft biometric information from forensic evidence is a highly relevant and pressing research area.

Among the various types of biometrics, fingerprints occupy a special position because they have a pattern that is unique to everyone and remains consistent throughout life. This uniqueness makes it one of the most reliable biometric identities in the authentication process [6]. In addition to functioning as a single identity [7], fingerprints also have fine morphological details that have been proven to have a statistical relationship with an individual's gender [8]. This finding shows that biological differences between men and women are also reflected in the micro characteristics of fingerprints [9]. Therefore, fingerprint pattern analysis is not only useful for identifying individuals but can also be used as a scientific basis in gender classification, a field that continues to develop in modern biometric studies.

One of the most frequently used traits is ridge density, which is the number of ridges per unit area [8], [10]. Females generally have a higher ridge density than males [5]. For example, values greater than 14 ridges/25 mm^2 are more likely to be female, while values less than 12 ridges/25 mm^2 are more likely to be male. This pattern has been found across populations [10]–[12], and is therefore thought to be universal. In addition, other traits such as the ridge thickness to valley thickness ratio (RTVTR), the number of white lines, and the asymmetry of the number of ridges have also been shown to be significant in distinguishing sex [5]. The combination of these characteristics forms a strong basis for automated classification systems.

Early attempts to automate gender classification from fingerprints generally used machine learning techniques. The process typically consisted of two stages of manual feature extraction, where researchers designed algorithms to compute features such as ridge density and RTVTR, and then fed the obtained features into standard classifiers [13], [14]. While these methods were quite successful, their performance was highly dependent on the quality and relevance of the manually engineered features, which were often unstable and difficult to generalize across different image conditions.

Advances in Deep Learning, particularly using convolutional neural networks (CNN), have had a significant impact on pattern recognition and computer vision. CNNs have the advantage of automatically extracting important features directly from pixel data without the need for complex feature engineering processes [15]. By utilizing convolutional, pooling, and fully connected layers, CNNs can form the most suitable data representation for classification tasks [16]. This approach not only simplifies the analysis process but also often results in better performance, as it is able to recognize detailed patterns that are difficult to capture using manual methods. The application of CNNs in fingerprint-based gender classification has demonstrated good performance, with many studies reporting high accuracy rates [13], [17]–[21]. However, most of these evaluations were conducted using high-quality fingerprint images acquired under controlled laboratory conditions. This creates a gap with real-world forensic conditions, where latent fingerprints are often incomplete, blurred, or distorted.

To address this challenge, the Sokoto coventry fingerprint dataset (SOCOFing) was developed by providing two types of images: real and altered, which mimic different forms of degradation [22]. Unfortunately, many previous studies do not explicitly specify the use of the Altered subset, resulting in widely reported results ranging from 72% [21] to 99% [23] and making them difficult to compare fairly. This study contributes by offering a transparent and practical training methodology. The entire SOCOFing dataset, both real and altered, is combined into a single unified dataset for training and testing. The main novelty of this approach is the demonstration that by explicitly training the model on diverse data, including both original and degraded images, CNNs can achieve high accuracy. This strategy establishes a strong baseline for practical forensic applications, as the model is not only tested for robustness after being trained on clean data, but is also trained to recognize various degradation conditions from the outset.

2. RELATED WORK

Advances in computing power have pushed deep learning, particularly CNNs, to become a leading approach in various image-based classification tasks. CNNs outperform traditional methods by automatically extracting important features directly from raw image data [15]. Various CNN architectures have been used for gender classification based on biometric data. For example, Habeeb *et al*. [24] applied efficient Net-B2, ResNet50, ResNet18, and Lightning architectures for gender prediction based on facial images, with ResNet18 achieving the highest accuracy of 98%. Kumar *et al*. [25] using AlexNet reported an accuracy of approximately 95.31% for gender prediction. Meanwhile, Arora *et al*. [26] shows that CNNs can achieve high accuracy even with low-quality input data. This finding suggests that architectures pre-trained on image datasets can be effectively adapted for specific tasks, such as gender classification from fingerprints, even with low-quality input data

Additionally, hybrid approaches have also been explored to combine the advantages of different methods. One example is the CNN-SVM framework, where the CNN serves as a feature extractor to capture spatial information from fingerprints, and the obtained features are then classified using SVM. This approach has been reported to achieve a very high accuracy of 99.25% on a given dataset, thus demonstrating the potential synergy between deep learning-based feature extraction and traditional classification methods [27].

The SOCOFing dataset, consisting of both real and altered images. However, the results of studies using this dataset show considerable variation, indicating the lack of a consistent evaluation protocol. For example, Oladele *et al*. [21] reported 72% accuracy using a simple seven-layer CNN. In contrast, Iloanusi and Ejiogu [27] used a deeper CNN with 20 layers and achieved 91.3% accuracy, indicating that architecture depth can impact model performance. Furthermore, Thonglim *et al*. [23] reported up to 99% accuracy with CNN consisting of only two convolutional layers, two pooling layers, and two dense layers. This contrasting range of results (72% to 99%) highlights the difficulty of direct comparisons between studies. One of the main factors causing the difference in results is the lack of clarity regarding the use of modified SOCOFing subsets in the training and testing. This lack of methodological transparency reinforces the need for more systematic and comprehensive studies. This study addresses this gap by combining all SOCOFing data, both real and altered, to build an inherently more robust model. With this approach, we aim to generate a robust baseline while ensuring fair comparisons of the results in the future.

3. METHOD

3.1. SOCOFing dataset

The dataset used in this study is SOCOFing which is a public biometric database [22]. This dataset is well-suited for our purposes because it provides both real and synthetically altered fingerprint images, allowing for robust model training. The dataset consists of 6,000 "real" fingerprint images collected from 600 subjects of African descent. Each subject contributed fingerprints from all ten fingers. One important component of the SOCOFing dataset is the Altered subset, which consists of tens of thousands of fingerprint images modified from the original (real) images. These modifications are performed using the STRANGE toolbox, which is designed to simulate various forms of forensic degradation. This subset is to simulate real damage conditions so that the robustness of the fingerprint recognition model can be tested more realistically. There are three main types of modifications in the Altered subset: central rotation (CR), obliteration (Obl), and z-cut (Zcut). Obliteration represents the effect of smearing or blurring on the fingerprint image, central rotation describes distortion due to torsion, while z-cut simulates physical damage such as scratches on the fingerprint surface. For example, the comparison of the thumb fingerprint between the real and altered images is shown in Figure 1. The original thumb fingerprint image was modified using the STRANGE toolbox to produce a degraded image with three levels of difficulty: easy, medium, and hard.

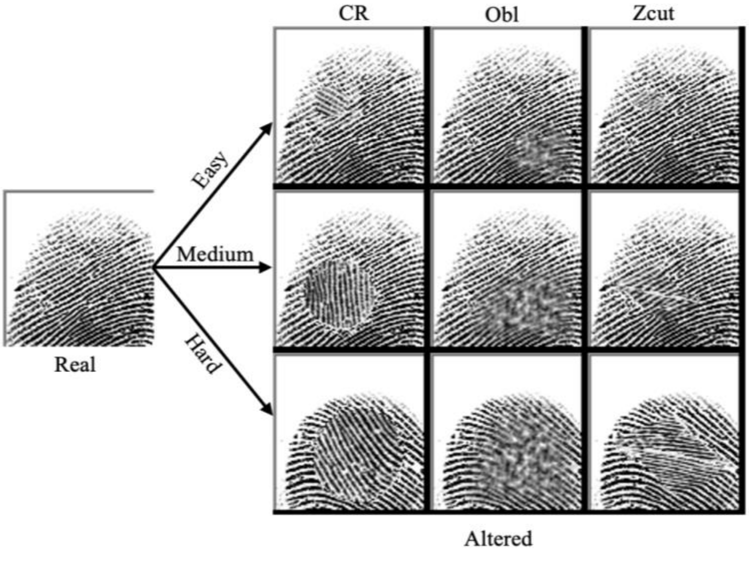


Figure 1. Illustration comparing the real thumbprint and degraded version of the same individual

3.2. Data preparation and preprocessing

To build a robust model, this study implemented an integrated and systematic data preparation workflow. The first crucial step is data merging. All images from the real directory and all altered sub-directories (altered-easy, altered-medium, and altered-hard) were merged into a single comprehensive dataset. All altered images represent degraded images. This data preparation strategy ensures that the model is trained on a wide variety of data, including both clean and degraded images.

After merging, the next step is label extraction. A custom script was developed to read the filename of each image in the merged dataset. The gender label was derived from specific characters in the filename and then converted into a numeric form by mapping male ('M') to 0 and female ('F') to 1. These numeric labels were then converted into a categorical format to match the loss function used in model training.

The next stage is image pre-processing. All images were first converted into grayscale format to ensure consistency of visual representation. After that, the images were resized to a uniform resolution of 96×96 pixels, which is chosen to balance computational efficiency and relevant morphological details. After that, pixel values are normalized by dividing each pixel value by 255.0, so that all values are in the range of 0 to 1. This normalization process helps stabilize training while accelerating model convergence. Next, the numeric labels are converted into a categorical format to match the loss function used.

After merging and preprocessing, all data is randomized and then divided into two parts: training (80%) and testing (20%). During the training process, a portion of the training data is also allocated as a validation set to monitor model performance and prevent overfitting. This separation strategy ensures that both the training and testing data have a representative distribution of both 'Real' and 'Altered' images, allowing for fair and consistent model evaluation.

3.3. Proposed CNN architecture

The primary goal of this research is to develop a model that not only achieves high accuracy but is also computationally efficient. To achieve this goal, this study proposes a multi-input CNN architecture. This model not only processes fingerprint images but also incorporates additional features into the decision-making process. The main branch of the model processes fingerprint images through three convolutional blocks. Each block consists of a Conv2D layer with ReLU activation and a MaxPooling2D layer. The number of filters is gradually increased from 32, 64, to 128, allowing the model to learn features from simple to complex. In addition to the image, the model also receives two additional inputs in the form of categorical features (hand type and finger type) which are processed using a separate Dense layer. Next, the results of the three branches the feature map from the flattened image and the output from the Dense layer for additional features are combined through a concatenate layer. This combined vector is further processed with a Dense layer containing 128 neurons, followed by a Dropout layer to prevent overfitting, and finally with an output layer containing two neurons for binary classification.

3.4. Training and evaluation protocol

To ensure fair and consistent evaluation, this study followed a clearly defined training and testing protocol. In this study, the model was built by utilizing the Keras framework running on TensorFlow as a backend, thus allowing the training process to be carried out efficiently and in a structured manner. Hyperparameter selection was based on best practices widely used in the literature. The model training process was performed using the Adam optimizer, combined with the categorical cross-entropy loss function, as it is suitable for multiclass classification tasks with softmax-based output. The learning rate was set at 0.001, while the maximum number of epochs was limited to 50, with an early stopping mechanism implemented to prevent overfitting. Furthermore, a batch size of 32 was used to maintain a balance between gradient stability and computational efficiency during training. Model performance evaluation was performed using standard metrics commonly used in classification tasks to provide a comprehensive overview of system performance. The metrics used include accuracy, precision, recall, and F1 score.

4. RESULTS AND DISCUSSION

4.1. Model performance on combined dataset

The model was trained using a training dataset containing a mix of 'real' and 'altered' images, then evaluated on a test dataset with a similar distribution. The evaluation results on the combined test dataset are shown in Table 1. Our model achieved an accuracy of 97.39%, demonstrating that training with diverse data, including degraded images, enables the CNN to learn robust feature representations that are resilient to various perturbations. The high results on this combined dataset are a key finding of the study, demonstrating that exposure to imperfect data during training is an effective strategy for building robust biometric models.

Table 1. Performance metrics on the combined dataset: real and altered images

Accuracy	Precision	Recall	F1-Score
0.9739	0.9437	0.9227	0.9331

4.2. Training curve analysis

To gain a deeper understanding of the model's learning process, we analyzed the training and validation accuracy curves over 50 epochs, as shown in Figure 2. The curves show the dynamics of model accuracy improvement on both the training data (shown by the blue line) and the validation data (shown by the orange line) as the number of epochs increases. In the early training phase, specifically around the first 10 to 15 epochs, there is a very sharp increase in accuracy, from around 80% to over 95%. This indicates that the model can quickly recognize and learn important patterns from fingerprint images.

After passing this initial phase, the accuracy curves began to flatten and showed a tendency towards convergence. Both training and validation accuracies stabilized at around 97–99%, indicating that the model had reached its optimal performance and that additional training no longer provided significant improvements. Furthermore, there was a small difference between the training and validation curves, with training accuracy slightly higher. The difference between training and validation accuracy remains within reasonable limits, thus not indicating overfitting. This is evident from the validation accuracy, which remains high and stable, with no signs of decline. This indicates that the model can perform well on new, previously unseen data. After passing the initial phase, the accuracy curve tends to flatten and reach a point of convergence. Both training and validation accuracy consistently hover in the range of 97–99%, indicating that the model has achieved optimal performance, so further training no longer provides significant improvement. This accuracy curve analysis is in line with the final evaluation results, which show that the model can be trained consistently, stably, and can achieve reliable high performance on test data.

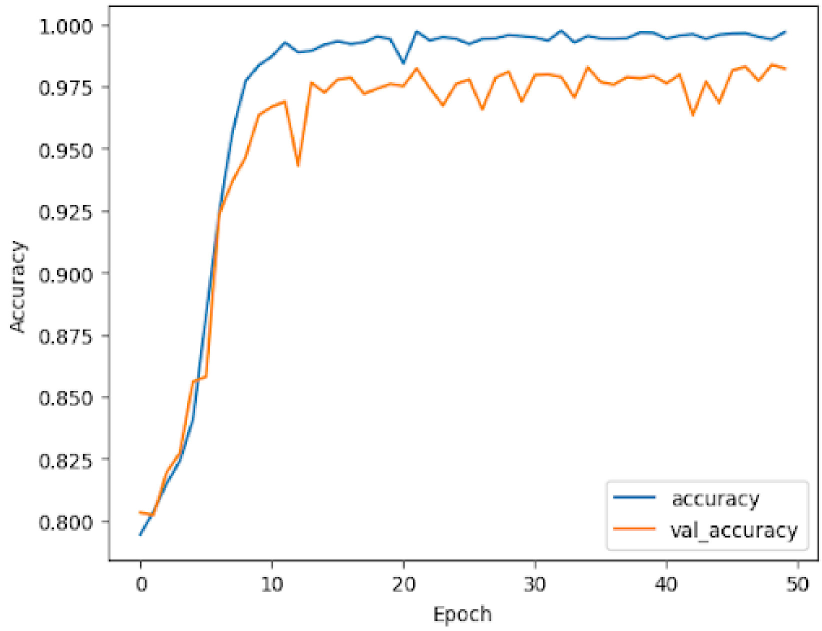


Figure 2. Training and validation accuracy curves

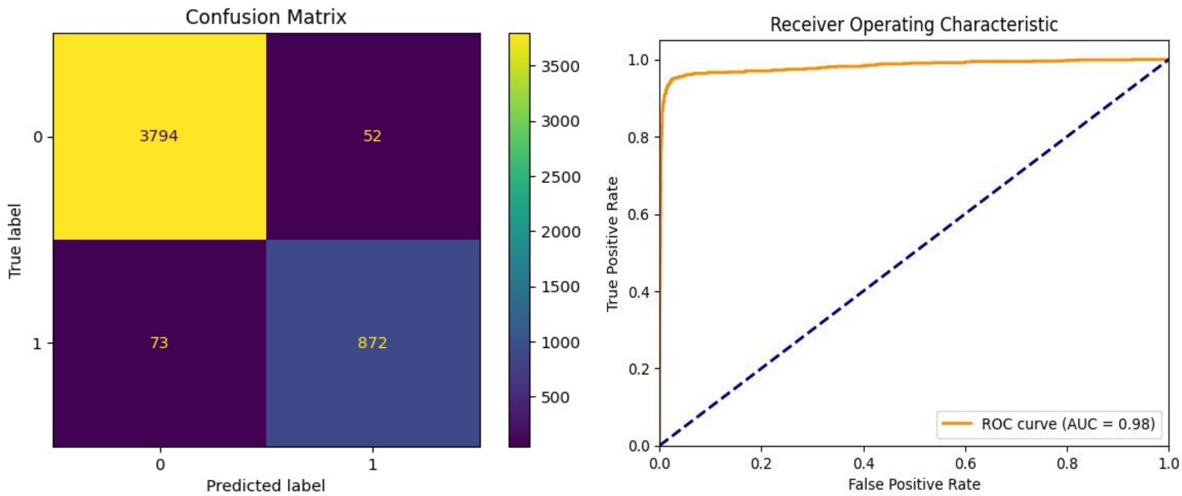
4.3. Confusion matrix and ROC curve analysis

For a more comprehensive evaluation in Figure 3, an analysis was performed using a confusion matrix and a receiver operating characteristic (ROC) curve, as shown in Figure 3(a). The confusion matrix provides a detailed overview of the distribution of model predictions. If class 0 represents one gender and class 1 represents the other, 3,794 class 0 samples and 872 class 1 samples were correctly classified. Conversely, only 52 class 0 samples were incorrectly detected as class 1, and 73 class 1 samples were incorrectly predicted as class 0. These results demonstrate that the number of correct predictions significantly outnumbers the number of errors, indicating a balanced model performance in recognizing both classes.

Furthermore, analysis using the ROC curve and the area under the curve (AUC) value shown in Figure 3(b) further corroborates these results. The ROC curve, indicated by the orange line, appears to curve sharply toward the upper left corner, away from the random diagonal line, indicating excellent model discrimination. The achieved AUC value was 0.98, close to the ideal value of 1.0. This means the model has a 98% probability of scoring a random positive sample higher than a random negative sample. Overall, the combination of the confusion matrix and ROC curve results demonstrates that the developed model not only achieves a high level of accuracy but also exhibits strong consistency and reliability in distinguishing between the two gender classes.

4.4. Advantages of training on aggregated data

The achieved accuracy of 97.39% on a test dataset consisting of a combination of clean and degraded images demonstrates highly significant results. This finding directly supports the main research hypothesis, namely that training CNNs on diverse and challenging datasets is an effective strategy for producing robust models. Rather than training the model only on data of perfect quality and hoping it will generalize to less-than-ideal data, this approach explicitly teaches the model to recognize essential features that remain consistent even when the image is smeared, distorted, or damaged. In this context, altered images can be viewed as a form of data augmentation specific to the biometric domain. While common augmentation techniques, such as random rotation or flipping, are often used to improve a model's generalizability, the use of alterations that mimic real-world forensic degradation, such as those found in the SOCOFing dataset, allows the model to learn a more invariant and practically relevant representation. The high accuracy achieved demonstrates that the model is not simply memorizing artifacts from altered data but is successfully extracting underlying patterns that are consistent across different image quality levels.



(a) (b)

Figure 3. Comprehensive evaluation in (a) confusion matrix and (b) ROC curve

4.5. Comparative analysis with relevant previous study

To place our results in the context of the existing literature, we compare our model's performance with results reported by other studies using the SOCOFing dataset. This comparison is presented in Table 2. Our model demonstrates very competitive performance, surpassing several previous studies that used only "real" data. While slightly below the 99% accuracy reported by Thonglim *et al*. [23] and Gustisyaf and Sinaga [28] with 99.9667% accuracy, it is important to note that our model was evaluated on an inherently more challenging dataset, as it includes both pristine and degraded images. This strongly suggests that our combined training approach produces a superior and more reliable model for practical applications.

It is important to note that the high performance achieved in this study was achieved using a relatively simple and computationally efficient architecture. This finding challenges the common assumption that only very deep and complex models can achieve state-of-the-art results. Our results confirm that data-related strategies, particularly the quality and diversity of training data, can be as important, or even more so, than the complexity of the network architecture itself.

The practical implications of these findings are significant, particularly in forensic contexts, where latent fingerprint quality is rarely ideal. Relying on models trained solely on high-quality laboratory data poses significant risks and results in less reliable systems. This research demonstrates that it is possible to build a single model that maintains high performance despite varying image quality. With the proposed training methodology, the developed system becomes more reliable when applied to real-world evidence from crime scenes. Its ability to process partially distorted images allows the model to still provide useful information for the investigation process. This has the potential to improve identification accuracy and overall efficiency in the forensic process, even when the available evidence is far from ideal.

Table 2. Comparison of model performance on the SOCOFing dataset in previous study

References	Dataset	Input	Model architecture	Accuracy
Oladele *et al*. [21]	Real	Only image	7-layer CNN (2 conv, 2 pool, 2 FC)	72%
Iloanusi and Ejiogu [27]	Real	Only image	20-layer CNN	91.3%
Thonglim *et al.* [23]	Real	Only image	CNN (2 donv, 2 pool, 2 dense)	99%
Gustisyaf and Sinaga [28]	Altered	Only image	CNN with ensemble and batch norm	99.9667%
Our model	Real+altered	Image+hand type +finger type	7-layer CNN (3 conv and MaxPooling, 4 dense)	97.39%

5. CONCLUSION

This research focuses on a critical challenge in forensic biometrics, namely the development of accurate and reliable fingerprint-based gender classification systems for real-world applications. Given that forensic evidence is rarely found in perfect condition, this research proposes and validates a training methodology that directly addresses the issue of data degradation. The proposed methodology combines raw fingerprint images and synthetically modified images from the SOCOFing dataset into a single, unified training set. The CNN model used is lightweight and computationally efficient yet achieves a very high accuracy of 97.39% on a test dataset that also includes a combination of clean and degraded images. This performance not only surpasses many previous studies but is also achieved under more realistic and challenging testing conditions. These findings emphasize that data strategy plays a key role in building robust models. By incorporating imperfect data into the training process, models can be developed to be inherently more robust and maintain high performance. This research also sets a new benchmark in fingerprint-based gender classification and provides a clear foundation for the development of more reliable biometric systems ready for use in real-world scenarios.

FUNDING INFORMATION

The implementation of this research was funded by LPPM Institut Teknologi Sains dan Kesehatan RS dr. Soepraoen Kesdam V/BRW to support the tridharma of higher education, especially in the aspects of research and scientific publication.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Risqy Siwi Pradini	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
Wahyu Teja Kusuma					✓	✓		✓	✓					✓
Agung Setia Budi	✓				✓					✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

DATA AVAILABILITY

The dataset used in this study was taken from paper [22]. The dataset is the Soko Fingerprint Dataset (SOCOFing), which contains fingerprint images in various conditions, including both real images and altered images with features such as obliteration, central rotation, and z-cut. This dataset is widely used in forensic biometrics research because it presents real challenges in fingerprint identification and classification.

REFERENCES

[1] S. A. Abdulrahman and B. Alhayani, "A comprehensive survey on the biometric systems based on physiological and behavioural characteristics," *Materials Today: Proceedings*, vol. 80, pp. 2642–2646, 2023, doi: 10.1016/j.matpr.2021.07.005.

[2] G. Singh, G. Bhardwaj, S. V. Singh, and V. Garg, "Biometric identification system: security and privacy concern," in *Artificial Intelligence for a Sustainable Industry 4.0*, Cham: Springer International Publishing, 2021, pp. 245–264, doi: 10.1007/978-3-030-77070-9_15.

[3] B. Hassan, E. Izquierdo, and T. Piatrik, "Soft biometrics: a survey," *Multimedia Tools and Applications*, vol. 83, no. 5, pp. 15151–15194, Mar. 2021, doi: 10.1007/s11042-021-10622-8.

[4] R. Thakur, S. Kumar, S. K. Singh, K. Singla, S. K. Sharma, and V. Arya, "Cyber synergy: unlocking the potential use of biometric systems and multimedia forensics in cybercrime investigations," *Digital Forensics and Cyber Crime Investigation: Recent Advances and Future Directions*, pp. 241–267, 2024, doi: 10.1201/9781003207573-12.

[5] F. B. Ibitayo, O. A. Olanrewaju, and M. B. Oyeladun, "A fingerprint based gender detector system using fingerprint pattern analysis," *International Journal of Advanced Research in Computer Science*, vol. 13, no. 4, pp. 35–47, Aug. 2022, doi: 10.26483/ijarcs.v13i4.6885.

[6] S. Hemalatha, "A systematic review on fingerprint based biometric authentication system," in *International Conference on Emerging Trends in Information Technology and Engineering, ic-ETITE 2020*, Feb. 2020, pp. 1–4, doi: 10.1109/ic-ETITE47903.2020.342.

[7] R. K. Verma *et al.*, "Zinc oxide (ZnO) nanoparticles: synthesis properties and their forensic applications in latent fingerprints development," *Materials Today: Proceedings*, vol. 69, pp. 36–41, 2022, doi: 10.1016/j.matpr.2022.08.074.

[8] S. Sharma, R. Shrestha, K. Krishan, and T. Kanchan, "Sex estimation from fingerprint ridge density: a review of literature," *Acta Biomedica*, vol. 92, no. 5, 2021, doi: 10.23750/abm.v92i5.11471.

[9] C. D. Anjana, C. V. Priyatha, and M. S. Siva Prasad, "A comparative study on friction ridge pore features of males and females," *International Journal of Biometrics*, vol. 16, no. 2, pp. 158–175, 2024, doi: 10.1504/IJBM.2024.137089.

[10] V. A. Chavan and R. Kumar, "Exploring the potential of ridge density as a measure of sex identification," 2020.

[11] D. Das *et al.*, "Sexual dimorphism and topological variability in fingerprint ridge density in a north-west Indian population," *The Science of Nature*, vol. 111, no. 3, p. 23, Jun. 2024, doi: 10.1007/s00114-024-01911-x.

[12] M. E. Nandi, O. Olabiyi, and O. Cletus, "Variation in thumbprint patterns and ridge density counts between two major ethnic groups in Nigeria," *Article in Journal of Experimental Medical Sciences*, 2021.

[13] L. Akter, M. A. Based, A. B. M. T. U. Islam, and E. U. Rahman, "Comparative analysis of fingerprint-based gender classification employing convolutional neural network," in *2024 Parul International Conference on Engineering and Technology, PICET 2024*, May 2024, pp. 1–5, doi: 10.1109/PICET60765.2024.10716057.

[14] L. Berriche, "Comparative study of fingerprint-based gender identification," *Genetics Research*, vol. 2022, pp. 1–9, Dec. 2022, doi: 10.1155/2022/1626953.

[15] J. Gupta, S. Pathak, and G. Kumar, "Deep learning (CNN) and transfer learning: a review," *Journal of Physics: Conference Series*, vol. 2273, no. 1, p. 012029, May 2022, doi: 10.1088/1742-6596/2273/1/012029.

[16] Purwono, A. Ma'arif, W. Rahmaniar, H. I. K. Fathurrahman, A. Z. K. Frisky, and Q. M. U. Haq, "Understanding of convolutional neural network (CNN): a review," *International Journal of Robotics and Control Systems*, vol. 2, no. 4, pp. 739–748, Jan. 2022, doi: 10.31763/ijrcs.v2i4.888.

[17] D. Arivalagan, K. Bhoopathy Began, S. Ewins Pon Pushpa, and K. Rajendran, "A novel intelligent 12-layer convolutional neural network model for gender classification using fingerprint images," *Journal of Intelligent and Fuzzy Systems*, vol. 45, no. 2, pp. 2685–2706, Aug. 2023, doi: 10.3233/JIFS-224284.

[18] G. Jayakala, L. Sudha, and A. Professor, "Gender classification based on fingerprint analysis," *Turkish Journal of Computer and Mathematics Education*, vol. 12, no. 10, pp. 1249–1256, 2021.

[19] O. S. Olufunso, A. E. Evwiekpaefe, and M. E. Irhebhude, "Determination of gender from fingerprints using dynamic horizontal voting ensemble deep learning approach," *International Journal of Advances in Intelligent Informatics*, vol. 8, no. 3, pp. 324–336, Nov. 2022, doi: 10.26555/ijain.v8i3.927.

[20] R. Singh, N. Sharma, R. Chauhan, A. Choudhary, and R. Gupta, "Enhanced fingerprint alteration detection using lightweight CNN model trained on SOCOFing dataset," in *2023 3rd International Conference on Smart Generation Computing, Communication and Networking, SMART GENCON 2023*, Dec. 2023, pp. 1–6, doi: 10.1109/SMARTGENCON60755.2023.10441980.

[21] M. O. Oladele, T. M. Adepoju, O. A. Olatoke, O. A. Ojo, and Orimogunje, "Convolutional neural network for fingerprint-based gender classification," *Sciences, Engineering & Environmental Technology (ICONSEET)*, vol. 7, no. 14, pp. 112–117, 2022.

[22] Y. I. Shehu, A. Ruiz-Garcia, V. Palade, and A. James, "Sokoto Coventry Fingerprint Dataset," Kaggle, Jul. 2018. [Online]. Available: https://www.kaggle.com/ruizgara/socofing.

[23] P. Thonglim, S. Thongsuwan, and P. Buranasiri, "Gender classification using convolutional neural networks based on fingerprint analysis with in-line digital holography," in *Quantitative Phase Imaging X*, Mar. 2024, p. 100, doi: 10.1117/12.3010005.

[24] M. A. Habeeb, Y. L. Khaleel, R. D. Ismail, Z. T. Al-Qaysi, and F. N. Ameen, "Deep learning approaches for gender classification from facial images," *Mesopotamian Journal of Big Data*, vol. 2024, pp. 185–198, Oct. 2024, doi: 10.58496/MJBD/2024/013.

[25] S. Kumar *et al.*, "Face spoofing, age, gender and facial expression recognition using advance neural network architecture-based biometric system," *Sensors*, vol. 22, no. 14, p. 5160, Jul. 2022, doi: 10.3390/s22145160.

[26] S. Arora, R. Mittal, H. Kukreja, and M. P. S. Bhatia, "An evaluation of denoising techniques and classification of biometric images based on deep learning," *Multimedia Tools and Applications*, vol. 82, no. 6, pp. 8287–8302, Mar. 2023, doi: 10.1007/s11042-021-11573-w.

[27] O. N. Iloanusi and U. C. Ejiogu, "Gender classification from fused multi-fingerprint types," *Information Security Journal*, vol. 29, no. 5, pp. 209–219, Sep. 2020, doi: 10.1080/19393555.2020.1741742.

[28] A. I. Gustisyaf and A. Sinaga, "Implementation of convolutional neural network to classification gender based on fingerprint," *International Journal of Modern Education and Computer Science*, vol. 13, no. 4, pp. 55–67, Aug. 2021, doi: 10.5815/IJMECS.2021.04.05.

BIOGRAPHIES OF AUTHORS

Risqy Siwi Pradini is a lecturer in the Informatics Study Program, Faculty of Science and Technology, ITSK Soepraoen. She earned a Bachelor of Applied Science degree from Politeknik Negeri Malang and a Master of Computer Science degree from Universitas Brawijaya. She is currently pursuing research in Information Systems, Machine Learning, and Deep Learning. She can be contacted at email: risqypradini@itsk-soepraoen.ac.id.

Wahyu Teja Kusuma is a lecturer at ITSK Soepraoen. He currently serves as the Head of the LPPM ITSK Soepraoen. He earned his bachelor's and master's degrees in computer science from Universitas Brawijaya. He is currently completing his doctoral program in computer science at Universitas Brawijaya. He can be contacted at email: wtkusuma@itsk-soepraoen.ac.id.

Agung Setia Budi is a Bachelor of Electrical Engineering graduate from Brawijaya University in 2009. He graduated from the Graduate School of Engineering, University of Miyazaki in 2012 and Master of Electrical Engineering, University of Brawijaya in 2013. He then continued his doctoral studies and graduated from the Interdisciplinary Graduate School of Agriculture and Engineering, University of Miyazaki in 2019. Currently, he is active as a lecturer at the Faculty of Computer Science, Brawijaya University. He can be contacted at email: agungsetiabudi@ub.ac.id.