Human Gender Classification Using Fingerprint Images

Abstract— **In forensic investigations, gender identification plays a vital role in helping to identify individuals involved in criminal activities. Accurate gender identification is hindered by problems such as incomplete or degraded biological samples and limited data. The aim is to develop an accurate deep-learning model of gender classification using altered low-quality images, to investigate the impact of various finger types, and to apply fingerprint reconstruction techniques. The Sokoto Coventry Fingerprint Dataset is utilized, featuring diverse fingerprint images with obliteration artificial modifications. Differences in ridge density between male and female fingerprints, with females having a higher density, have been identified as a key finding, which helps to identify the gender accurately. In demonstrating its potential for forensic use, the gender classification model achieved an excellent accuracy score of 94.84%. The classification of the finger types also shows a high accuracy of 92.39%, indicating the reliability. As demonstrated by the low mean Squared Error score and the high Structural Similarity Index score, the reconstruction of fingerprints using autoencoder models significantly improves the image quality to address practical limitations in the acquisition of clear images. These findings contribute to the development of techniques for identifying gender in forensic science, and in biometric analysis during criminal investigations. Future directions include refining feature extraction and classification models for accurate gender classification across diverse demographics, such as individuals from various countries and regions. Additionally, advancing fingerprint reconstruction techniques aims to overcome practical limitations in forensic image acquisition, enhancing overall gender classification accuracy in forensic science and biometric analysis.**

Keywords— Human gender classification, Deep learning, Fingerprint Reconstruction, Autoencoder, Forensic image acquisition

I. INTRODUCTION

In forensic investigations, gender identity is essential as it helps identify and profile those who are involved in criminal activity. However, there are a number of obstacles that make it difficult to accurately determine gender in forensics. These include incomplete or degraded biological samples, limited available information, and the need for reliable and efficient methods. Examining biological evidence such as fingerprints, DNA samples, skeletal remains, and other biometrics like facial photos, iris patterns, and hand shapes is frequently necessary for gender identification in forensic investigations [1].

These methods have various benefits and drawbacks, and they might not always be practical or definitive in forensic situations. Given the potential applications of these biometric modalities in forensic gender identification, it is imperative to address the difficulties specific to each modality and create strong procedures capable of overcoming current limitations. Fingerprints are a unique type of biometric identification that are distinguished by their characteristic ridge and valley patterns as shown in Fig. 1. Because these patterns, which consist of valleys as white spaces between neighboring ridges and ridges as black lines, remain constant throughout an individual's life, fingerprints are extremely trustworthy for identification. Fingerprints are unique, meaning that every person has a different pattern, and they are immutable, meaning that these patterns will be true across time [2].

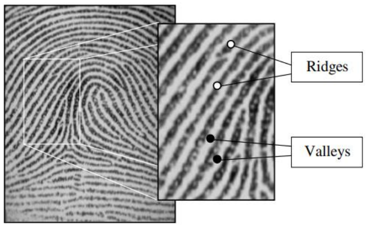

Fig. 1. Ridges and valleys on a fingerprint image

Within the fields of forensic anthropology and criminal investigations, a person's gender can be ascertained by a variety of biometric modalities, including fingerprints, which are particularly useful for classifying and recognizing a person's gender. Gender classification using fingerprints is especially important since it helps reduce the number of people on suspect lists and makes it easier to identify those who are committing crimes. This study focuses on altered fingerprint images as shown in with varying forms in an effort to use fingerprint analysis as a biometric tool for gender classification. This work tackles the problem of gender classification from blurry and altered fingerprint photos because of practical limitations in acquiring high-quality images, particularly in forensic circumstances. This research explores the complexity of gender classification using altered photos as shown in Fig. 2, mirroring real-world forensic challenges, in contrast to many previous studies that only focus on classifying gender using clear and quality photographs.

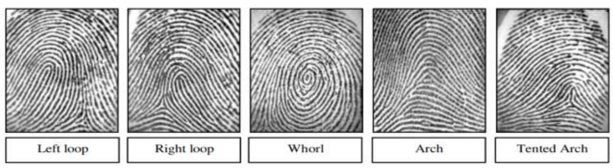

Fig. 2. fingerprint ridge patterns of the five major classes

The main objective of this research is to develop a solid and effective methodology for gender identification in forensic investigations utilizing fingerprint image analysis. This methodology was created for handling issues associated with insufficient or degraded biological specimens and restricted availability of data in forensic situations. The following represent a specific objectives of the study:

- Using changed, low-quality images, construct an accurate deep learning model specifically for gender classification.
- Analyzing how different finger types and characteristics affect the accuracy of gender classification.
- Implementing fingerprint reconstruction techniques to enhance the quality and usability of altered fingerprint images.

II. Background and Related Work

Deep neural network models have been demonstrated to accurately evaluate images of human faces and recognize a variety of features, including age, gender, and emotional state [3]. The researchers examined the facial features that were used to predict gender and age using Layer-wise Relevance Propagation. According to a different study, GoogLeNet outscored the two datasets (WIKI and Caltech Faces) in terms of classification accuracy [4]. Regardless of the learning rate applied, it obtained an accuracy of 92.57% for WIKI (cleaned) and 88.89% for Caltech Faces. The researchers also noted that further improvements in classification accuracy can be achieved by adjusting network parameters, modifying the network structure, and employing more advanced data augmentation techniques.

For biometric recognition and associated applications in artificial intelligence, machine learning, and pattern recognition, the biometric community has mostly studied face and hand modalities. Hand-based traits, such as palmprint, fingerprint, and hand geometry, have received significant research interest, offering the potential for personal verification as both conventional and soft biometric traits [5]. Another study uses artificial neural networks (ANNs) and digital image processing to distinguish between genders based on fingerprint samples [6]. Following the application of preprocessing procedures, six phases of the Discrete Wavelet Transform (DWT) were used to extract features. Using a dataset of 200 left thumbprint pictures with equal distributions of male and female fingerprints, the artificial neural network (ANN) based on backpropagation gathered 78% accuracy for male fingerprint recognition and 82% accuracy for female fingerprint identification.

The image preprocessing is a major part of the image classification and normalization [7], binarization, complement image, and filtering can apply to enhance quality. The study utilized principal component analysis (PCA) and fast Fourier transform (FFT) to extract features, subsequently min-max normalization in the fingerprint dataset to train using individual features and their fusion, achieved classification accuracy levels of 75.55% for males and 91.62% for females [8].

A. *Autoencoder-Based Approaches*

A particular Dense Dilated Convolution ResNet Autoencoder (DDC-ResNet) architecture for gender classification based on fingerprints has been suggested in recent study [9]. By studying the impact of the finger, this technique uses convolutional approaches to extract highly accurate gender-specific features. It was discovered that the right ring finger was the most helpful in classifying gender. Certain features were shown to be essential to gender disparity in fingerprints, including the geometries of loops and whorls, bifurcations, and lines. These results illustrate how effectively autoencoders perform feature extraction for gender classification with an accuracy of 96.5%.

B. *Ensemble Learning Approach*

In a study [10], a deep convolutional neural network (CNN) model is used to demonstrate a dynamic ensemble selection approach for gender classification based on fingerprints. This approach dynamically selects high-performing models based on validation accuracy by using horizontal voting ensembles. Histogram Equalization is a technique used for distributing pixel intensity values and enhance the contrasting qualities of fingerprint photographs.

C. *Deep Learning Approaches*

One study explores the application of the thumb convolutional neural network (TCNN) [11] for finger-type classification using two fingerprint datasets. The study achieves average of 96.5% accuracy by employing data augmentation and model optimization techniques. Thinning techniques, ROI segmentation, ridge orientation, and binarization to enhance the fingerprint images. These strategies empower the CNN-based approach to classify law-quality images with robust feature learning capabilities, underlining the reliable biometric identification systems.

Another significant contribution integrates a pre-trained deep learning architecture (EfficientNetB0) with machine learning techniques for fingerprint classification [12]. The approach achieves remarkable efficiency and 99.91% accuracy in challenges involving gender classification. With less training time, this approach presents an appealing option for fingerprint categorization. The accomplishments of a study not only exceed current methods for classifying fingerprints based on gender, but they also open the way for practical uses where accuracy and speed are crucial.

Based on fingertip size and fingerprint ridge count, an investigation focuses into gender classification [13]. A study discovered that across all age groups, men's fingerprints have larger fingertip sizes than women's. Even with law-quality fingerprints, this method's simplicity reveals its reasonable accuracy and low computational complexity, making it a workable approach for gender classification. Another study explores fingerprint gender classification using a specific type of decision tree algorithm (univariate decision tree or J48) [14]. The study utilizes four types of fingerprint features, namely Ridge Count (RC), Ridge Density (RD), Ridge Thickness to Valley Thickness Ratio (RTVTR), and White Lines Count (WLC) as shown in Table 1.

Table 1. Mean values of the four fingerprint features

Feature	Female	Male
Ridge Density (RD)	0.65	0.47
Ridge Thickness to Valley Thickness Ratio (RTVTR)	0.81	0.54
Ridge Count (RC)	16.34	11.71
White Lines Count (WLC)	17.38	11.18

D. Hybrid Approaches

A study investigated into an approach that merged fingerprint global-level features that were extracted using traditional methods with multilayer perceptron neural networks (MLPNN) [15], a type of deep learning architecture, with fingerprint global-level features extracted using traditional methods. The study found that women tend to have higher Ridge Density, higher white lines count, and higher ridge thickness to valley thickness ratio compared to men, consistent with previous studies.

III. Materials And Methods

The primary dataset of the study is the Sokoto Coventry Fingerprint Dataset (SOCOFing) [16], which concentrates on gender classification using fingerprint images. SOCOFing is a specifically chosen biometric fingerprint database designed with academic research projects. With 6,000 fingerprint pictures collected from 600 African people, it is a thorough collection that guarantees a representative and varied sample. Among its distinctive features is that SOCOFing explicitly labels the hand and finger names as well as the gender. Additionally, the dataset includes artificially modified fingerprint photos with different levels of alterations, such as obliteration, central rotation, and z-cut. The utilization of SOCOFing as the dataset underpins the robustness and relevance of the research findings in the context of gender classification in fingerprint analysis.

A. Image segmentation

The efficacy of the thresholding technique for image segmentation is explored, Otsu's thresholding is an automatic technique that uses the image histogram to select the ideal threshold value, producing better segmentation outcomes as shown in Fig. 4. Otsu's approach is a useful tool for image processing tasks since it is capable of adapting to different lighting conditions and background noise, which often results in a superior implementation. To improve the segmentation process, these techniques are used after the image boundaries have been removed.

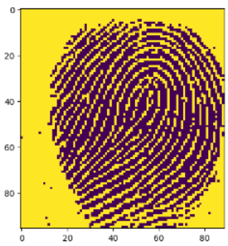

Fig. 4. Otsu's thresholding

Determining the ideal threshold to optimize the intensity level gap between foreground and background pixels is the basic notion underlying Otsu's method [17]. With the use of this ideal threshold, the image is effectively split into two classes: background pixels, which are pixels with intensities below the threshold, and foreground pixels, which are pixels with intensities above the threshold. In order to ensure distinct discrimination between image regions, the algorithm calculates a threshold value by examining the pixel intensity histogram and minimizing intra-class variation while increasing inter-class variance.

B. Ridge density

The ridge density analysis that follows provides a numerical way to distinguish between fingerprints belonging to various genders based on the distinctive ridge patterns. Preprocessing methods were used to examine the ridge density of fingerprint images, both male and female, in the dataset. To create a binary image that represents various ridge details, these processes involve compressing the image, translating it to an 8-bit unsigned integer format, and using Otsu's thresholding to obtain a binary image representing different ridge minutiae. The regions that indicate different forms and the ridge patterns specific to the fingerprints of men and women are both measured by the average ridge density [18]. These regions classified into three topologies called Loop, Whorl, and Delta as shown in Fig. 3.

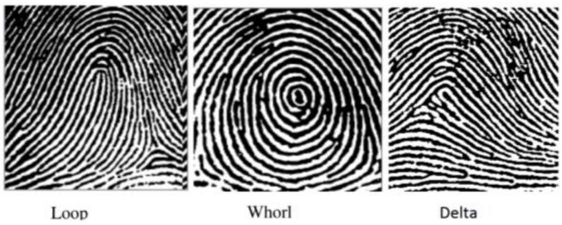

Fig. 3. Common topologies of fingerprint

The ridge density distribution for male and female fingerprints is obtained by basically counting the pixels in the fingerprint picture that are considered to be part of the ridges and dividing that total number by the number of pixels in the image.

C. Ridge length

Using contour analysis, the ridge lengths of both male and female fingerprints were determined as shown in Fig. 5. Following the gender-based ridge length separation, statistically ridge length is computed. The resulting statistics show that the ridge lengths of male and female fingerprints differ significantly. For example, the average ridge length of males is at 7.74 units, whereas the average ridge length of females is slightly longer at 9.56 units. These results offer important new understandings of the gender-based structural differences in ridge patterns in fingerprint analysis. It is imperative to acknowledge that disparities in data quality may cause these conclusions to be off from the true ridge lengths in practical situations. Ridge lengths that are computed can be greatly affected by variables like overall image quality, preprocessing methods, and image resolution. Significant variability in computed ridge lengths can also be attributed to changes in fingerprint area sizes within the dataset.

Fig. 5. Sample Ridge length on Fingerprint Image

D. Gender Classification

The gender classification model presented in this study focuses on using altered fingerprint images as the dataset for training and evaluation. This decision stems from the practical considerations surrounding the availability and quality of real fingerprint images, especially in scenarios such as criminal investigations where obtaining high-quality images can be challenging. Manual methods have traditionally been employed to enhance the quality of real fingerprint images; however, this study aims to address the practicality aspect by evaluating gender classification performance using altered images. By leveraging altered fingerprint images, this approach seeks to emulate real-world scenarios where the quality of images may be compromised, thereby enhancing the model's applicability in practical use cases.

For gender classification using altered fingerprint images, a convolutional neural network (CNN) architecture was employed as shown in Fig. 6. The CNN model is made up of multiple layers that are intended to take features out of the input images and use them to learn discriminative patterns. The architecture begins with a convolutional layer followed by max-pooling layers, which help in capturing spatial information and reducing dimensionality, respectively.

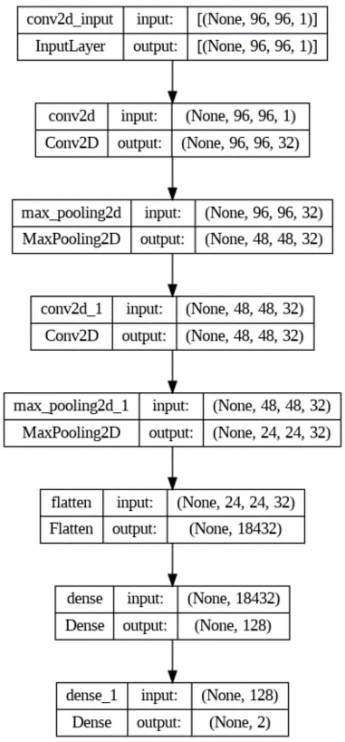

Fig. 6. Convolutional Neural Network (CNN) architecture

E. Finger type classification

The finger types of human hand include thumb finger, index finger, middle finger, ring finger, and little finger.The model is designed as a conventional CNN, with convolutional layers performing feature extraction, pooling layers performing spatial downsampling, and fully connected layers performing classification. The output layer's softmax activation makes sure that the model generates probabilities for every type of finger, with the predicted class having the highest probability.

F. Reconstruct fingerprints using autoencoder

Fingerprints may suffer from noise, distortion, or low resolution due to various factors like image acquisition conditions or image processing. Reconstructing them helps to enhance their quality, making them more suitable for accurate analysis and identification. One kind of artificial neural network that can be utilized for fingerprint reconstruction is an autoencoder. Autoencoder-based data denoising is very useful for processing modified images. Due to a variety of circumstances, including picture acquisition conditions or purposeful modifications like obfuscation or rotation, these altered photos frequently contain noise or distortion. In these kinds of situations, autoencoders can learn to reduce noise and bring back the original information in order to reconstruct clean versions of the previously modified images. By enhancing the quality of the modified photos, this denoising feature helps make them better suited for activities involving analysis, comparison, or recognition.

In this study, an autoencoder architecture is utilized to reconstruct fingerprints from a dataset consisting of 6000 images as shown in Fig. 7. The aim was to develop a robust method capable of restoring original fingerprint details from altered or noisy images, thereby enhancing the accuracy and reliability of fingerprint analysis.

In contrast, the decoder part consists of up-sampling layers and convolutional layers with matching filter sizes (128, 64) to recreate the fingerprint pictures. Reconstructing the spatial information and patterns that the encoder learnt is the goal of the decoder's convolutional layers. The last layer creates a binary output that represents the restored fingerprint image using the sigmoid activation function. Using optimization methods such stochastic gradient descent and Adam optimizer, the model was trained to reduce the reconstruction error between the input and output images.

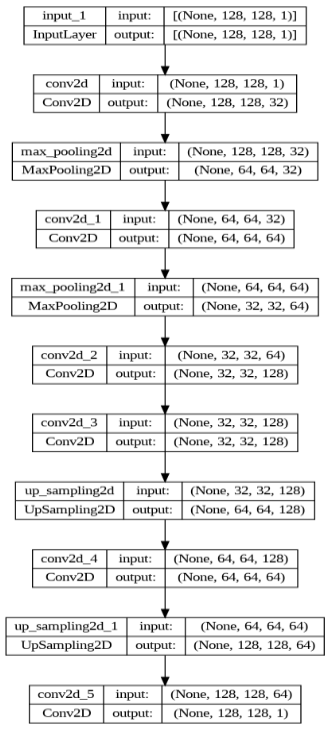

Fig. 7. Encoder-decoder network for Fingerprint *reconstruction*

IV. Results And Discussion

A. Gender Comparison based on ridge density

In the dataset, females have an average ridge density of roughly 0.313, which is somewhat higher than males' average of 0.275 as shown in Fig. 9. This suggests that compared to male fingerprints, female fingerprints typically show a richer collection of ridge patterns.

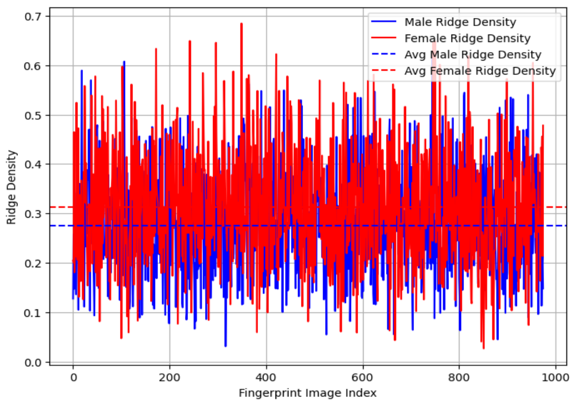

Fig. 9. Sample Ridge Density Distribution for Male and Female Fingerprints

B. Classification of Gender and the Finger Type

This analysis focuses on evaluating the performance of the gender classification model trained on altered fingerprint images. The results highlight the model's ability to generalize to unseen data and its overall performance in gender classification tasks. With an accuracy score of 0.9484, the model has demonstrated impressive performance in accurately predicting gender from altered fingerprint images as shown in Fig. 10 . With this score, the model's predictions agree on almost 94.84% of the test set. With such a high accuracy score, the model has demonstrated its ability to effectively learn complex patterns and important properties from the training set, allowing it to provide extremely accurate predictions on novel, unobserved data instances.

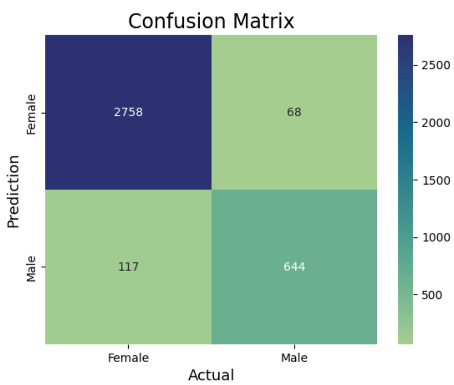

Fig. 10. Confusion Matrix for gender classification

The training and validation curves of the gender classification model exhibit desirable characteristics, indicating that the model was trained effectively and can predict gender with a high degree of accuracy as shown in Fig. 8. Identifying finger types is a crucial subject with many applications in the field of fingerprint analysis and identification. A key component of personal identification is the capacity to distinguish between the thumb, index, middle, ring, and little fingers from fingerprint scans

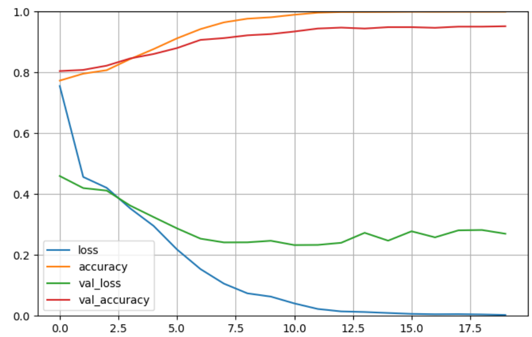

Fig. 8.Training and Validation Performance of Gender Classification Model

. As shown in Fig. 11 The CNN approach's resilience and reliability for classifying finger types are demonstrated by the high accuracy of 92.39%, which showcasing its potential for practical applications in fingerprint analysis.

Fig. 11. Confusion matrix for finger type classification

C. Fingerprint Reconstruction

One of the most important parts of fingerprint analysis is fingerprint image reconstruction, which greatly improves image quality and helps extract useful information for identification. The trained CNN model performed remarkably well when it came to reconstructing fingerprints. Noise and distortion seen in altered photos were successfully removed from the reconstructed images, which showed excellent faithfulness to the initial fingerprints. The regenerated fingerprint images are different from the ground truth images on average by a minimal amount, according to the Mean Squared Error (MSE) value of 0.01. This low mean square error (MSE) indicates that the autoencoder model has successfully learned to recreate the fingerprint images with minimum distortion and high accuracy. The quality of the reconstructed pictures is further supported by the Structural Similarity Index (SSIM) score of 0.91. Based on luminance, contrast, and structure, SSIM calculates how similar two images are to each other; values nearer 1 denote greater similarity. The SSIM score in this instance shows a high degree of similarity between the ground truth and rebuilt mages, indicating that significant structural details were preserved during the reconstruction process as shown in Fig. 12.

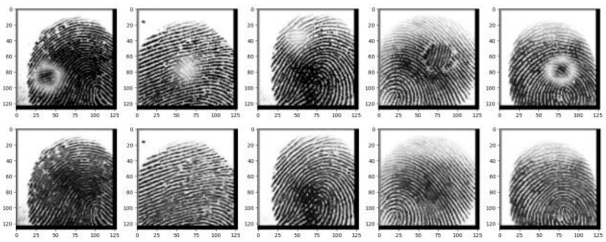

Fig. 12. Altered vs reconstructed fingerprints

D. Discussion

The observed variation in ridge density between male and female fingerprints has important consequences for the accuracy of gender determination. A denser and more complex arrangement of ridge patterns is suggested by a higher ridge density in female fingerprints, which enhance the accuracy of gender classification algorithms. The variations in ridge density across genders could be attributed to biological variables such genetic variants and hormonal impacts, but more biological research is required to establish conclusive linkages. The gender classification model performed admirably, correctly identifying the gender from modified fingerprint photos. The model exhibits strong validation metrics and a high accuracy score, making it suitable and reliable for use in real-world scenarios. This is especially true for forensic investigations where gender identification from fingerprint data is required.

The autoencoder model's strong Structural Similarity Index (SSIM) score and low Mean Squared Error (MSE) value demonstrate how well it reconstructs fingerprint pictures and improves image quality. The forensic analysis and biometric identification systems, where precise and clear fingerprint pictures are necessary for trustworthy identification and feature analysis, will be greatly impacted by this successful reconstruction. In many applications, the model's capacity to eliminate noise and distortions enhances the general quality and dependability of the data

V. Conclusion An Future Works

This study shows excellent accuracy and reliability in various tasks and offers insightful information on finger type classification, gender classification, and fingerprint reconstruction using altered images. The results highlight how well the suggested approaches and models address the research objectives, especially in the areas of forensic investigations and biometric identity systems. It is imperative to acknowledge the limits of the study, which include variances in image quality, diversity of datasets, and complexity of real-world gender classification scenarios. Addressing these limitations will be crucial for advancing the applicability and robustness of the proposed methodologies in practical settings.

Subsequent investigations ought to concentrate on resolving the recognized constraints in order to augment the efficacy and relevance of the suggested approaches. This entails growing the dataset to include a wider variety of demographics, raising the bar for image quality, and enhancing the models to better handle scenarios involving complex gender classification. Further investigating sophisticated feature extraction methods, combining multimodal biometric data, and applying deep learning techniques may enhance the precision and dependability of gender categorization and fingerprint reconstruction models. Working together, academic institutions and industry players can also make it easier to create practical applications that take use of these developments in forensic science and biometric analysis.

References

[1] "Faces, Fingerprints & Feet Guidance on assessing the value of including biometric technologies in UNICEF-supported programs," 2019.

[2] "Fingerprint Analysis and Representation," in *Handbook of Fingerprint Recognition*, New York: Springer-Verlag, pp. 83–130. doi: 10.1007/0-387-21587-5_3.

[3] S. Lapuschkin, A. Binder, K.-R. Müller, and W. Samek, "Understanding and Comparing Deep Neural Networks for Age and Gender Classification," Aug. 2017.

[4] Md. M. Islam, N. Tasnim, and J.-H. Baek, "Human Gender Classification Using Transfer Learning via Pareto Frontier CNN Networks," *Inventions*, vol. 5, no. 2, p. 16, Apr. 2020, doi: 10.3390/inventions5020016.

[5] R. Mukherjee, A. Bera, D. Bhattacharjee, M. Nasipuri, and N. A. Given, "Human Gender Classification Based on Hand Images Using Deep Learning," 2021.

[6] M. Kanojia, N. Gandhi, L. J. Armstrong, and C. Suthar, "Fingerprint Based Gender Identification Using Digital Image Processing and Artificial Neural Network," 2018, pp. 1018–1027. doi: 10.1007/978-3-319-76348-4_98.

[7] A. Badawi, M. R. Mahfouz, and R. Jantz, "Fingerprint-Based Gender Classification. Functional evaluation of men with BPH View project DCP 2.0 View project," 2006. [Online]. Available: https://www.researchgate.net/publication/220809166

[8] L. Berriche, "Comparative Study of Fingerprint-Based Gender Identification," *Genet Res (Camb)*, vol. 2022, 2022, doi: 10.1155/2022/1626953.

[9] Y. Qi, M. Qiu, H. Jiang, and F. Wang, "Extracting Fingerprint Features Using Autoencoder Networks for Gender Classification," *Applied Sciences (Switzerland)*, vol. 12, no. 19, Oct. 2022, doi: 10.3390/app121910152.

[10] 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.

[11] Y. A. Al-Wajih, W. M. Hamanah, M. A. Abido, F. Al-Sunni, and F. Alwajih, "Finger Type Classification with Deep Convolution Neural Networks," in *Proceedings of the International Conference on Informatics in Control, Automation and Robotics*, Science and Technology Publications, Lda, 2022, pp. 247–254. doi: 10.5220/0011327100003271.

[12] J. A. Alhijaj and R. S. Khudeyer, "Integration of EfficientNetB0 and Machine Learning for Fingerprint Classification," *Informatica*, vol. 47, no. 5, May 2023, doi: 10.31449/inf.v47i5.4724.

[13] P. Gnanasivam and R. Vijayarajan, "Gender classification from fingerprint ridge count and fingertip size using optimal score assignment," *Complex and Intelligent Systems*, vol. 5, no. 3, pp. 343–352, Oct. 2019, doi: 10.1007/s40747-019-0099-y.

[14] S. F., A. F. N. A. Rahman, Z. A. Abas, and W. H. M. Saad, "Fingerprint Gender Classification using Univariate Decision Tree (J48)," *International Journal of Advanced Computer Science and Applications*, vol. 7, no. 9, 2016, doi: 10.14569/ijacsa.2016.070931.

[15] S. F. Abdullah, A. F. N. A. Rahman, Z. A. Abas, and W. H. M. Saad, "Multilayer perceptron neural network in classifying gender using fingerprint global level features," *Indian J Sci Technol*, vol. 9, no. 9, Mar. 2016, doi: 10.17485/ijst/2016/v9i9/84889.

[16] Y. I. Shehu, A. Ruiz-Garcia, V. Palade, and A. James, "Sokoto Coventry Fingerprint Dataset," Jul. 2018.

[17] G. C. Wan, H. Xu, F. Z. Zhou, and M. S. Tong, "Improved Fingerprint Segmentation Based on Gradient and Otsu's Method for Online Fingerprint Recognition," in *2019 PhotonIcs & Electromagnetics Research Symposium - Spring (PIERS-Spring)*, IEEE, Jun. 2019, pp. 1050–1054. doi: 10.1109/PIERS-Spring46901.2019.9017405.

[18] D. Jomaa, "Fingerprint Segmentation."