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"Gender Classification Based on Biometric"

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Abstract: Biometric systems, particularly fingerprint recognition, are crucial for modern security and identity management. While traditionally used for authentication, recent research suggests that fingerprint characteristics can exhibit gender-specific differences. This paper explores the potential of machine learning techniques to classify an individual's gender based solely on fingerprint images. The approach involves systematically analyzing morphological features such as ridge density, ridge thickness, total ridge count, minutiae distribution, and overall texture patterns. This research aims to contribute to the expanding applications of fingerprint biometrics beyond traditional identification.

Keywords: Fingerprint Recognition, Gender Classification, Machine Learning, Biometrics, Feature Extraction, Pattern Recognition.

I. INTRODUCTION

Fingerprint recognition stands as a fundamental biometric modality, underpinning contemporary security, forensic, and identity verification systems due to its inherent accuracy and reliability in individual identification through unique physiological traits. The widespread adoption of fingerprint biometrics is attributed to the distinctiveness and permanence of fingerprint patterns, coupled with the feasibility of fingerprint data capture. While traditional fingerprint analysis has primarily focused on authentication, establishing identity through minutiae points and ridge patterns, burgeoning research explores the potential for extracting additional information, notably gender, from the intricate fingerprint patterns.

Studies suggest statistically significant morphological variations in fingerprints between genders, encompassing features like ridge density (with females tending to have higher ridge density), ridge thickness, minutiae distribution, ridge count, and textural patterns. These features, while present, pose challenges for traditional gender classification methods that rely on manual analysis, which can be time-consuming and prone to inaccuracies.

Recent research, such as the "Gender Detection and Classification from Fingerprints Using Convolutional Neural Network" study presented at ICSPC 2023, introduces automated approaches like Fig-Net, a CNN-based model designed to automate feature extraction and gender classification from fingerprint images, overcoming the limitations of manual analysis. CNNs, with their ability to automatically learn discriminative features, have shown promise in various fingerprint analysis tasks, including gender classification, identification, and liveness detection.

Complementary research explores alternative computational methods like Fuzzy C-Means (FCM) clustering, which, as highlighted in "Design of Fingerprint-Based Gender Clustering Using Fuzzy C-Means Algorithm," demonstrates high accuracy and robustness in gender classification by leveraging extracted fingerprint features and its ability to handle the inherent uncertainties in biometric data. FCM's strength lies in its "soft" classification approach, acknowledging that fingerprints can exhibit characteristics of both genders, offering a more nuanced analysis compared to "hard" classification methods.

These advancements, employing deep learning and fuzzy logic, signify a move towards leveraging machine learning to expand the applications of fingerprint biometrics beyond traditional identification and authentication, with potential benefits in forensic science, security systems, and demographic analysis.

II. LITERATURE SURVEY

Fingerprints have long been recognized as one of the most robust, unique, and reliable forms of biometric identification, extensively utilized in domains such as forensic science, civil identity verification, and security systems. Their inherent

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permanence and individuality make fingerprints ideal for personal identification. Traditionally, gender classification from fingerprints has been approached through manual or semi-automated methods, with researchers analyzing specific morphological traits such as ridge density, total ridge count, minutiae distribution, and the ratio of ridge thickness to valley spacing. These features are believed to show statistically significant variations between male and female fingerprints, largely due to physiological differences in finger size, ridge breadth, and skin texture. However, while these handcrafted approaches have laid the foundation for biometric gender recognition, they present considerable limitations. Manual analysis is not only labor-intensive and time-consuming but also subject to inconsistencies and human error, especially when dealing with degraded, partial, or noisy fingerprint images. Moreover, these conventional methods often struggle to generalize across diverse populations and fingerprint acquisition conditions.

To address these limitations, researchers have increasingly turned toward automated, data-driven approaches that leverage the power of machine learning—particularly deep learning. One prominent study, presented at the 2023 International Conference on Signal Processing and Communication (ICSPC), introduced a novel model called Fig-Net. This architecture is built upon Convolutional Neural Networks (CNNs), which are particularly well-suited for imagebased classification tasks due to their ability to learn spatial hierarchies of features directly from raw pixel data. Fig-Net is designed specifically for the task of gender classification using fingerprint images, and it automates both feature extraction and classification. The architecture of Fig-Net includes three convolutional layers interleaved with three maxpooling layers, followed by two fully connected layers for decision-making. The first convolutional layer (C1) employs a 7×7 kernel to extract low-level fingerprint characteristics such as edges, ridge contours, and fine-scale textures. The subsequent layers (C3 and C5), with 5×5 and 3×3 kernels respectively, capture higher-level abstractions and more complex spatial relationships indicative of gender-related structural differences. This progressive feature hierarchy enables the model to differentiate subtle biometric patterns that are often invisible to human observers or difficult to quantify through traditional statistical methods. Additionally, by training on large labeled datasets, CNN-based models like Fig-Net can learn discriminative features that are robust to variations in rotation, scale, and noise.

In addition to deep learning strategies, alternative computational intelligence techniques have also been explored, particularly clustering algorithms such as Fuzzy C-Means (FCM). Unlike hard clustering methods like K-Means, FCM assigns degrees of membership to each data point across multiple clusters, allowing it to better model the inherent ambiguity and overlapping characteristics in biometric data. This is especially advantageous in gender classification, where fingerprint traits may not always present clearly dichotomous patterns. In typical FCM-based fingerprint classification pipelines, researchers first perform preprocessing to enhance fingerprint quality and normalize orientation. Feature extraction is then carried out using metrics such as ridge count, ridge orientation, minutiae type (bifurcation, termination), and angular distribution of ridges. To enhance discriminatory power, some studies integrate Discrete Wavelet Transform (DWT) to extract texture features at multiple frequency levels, capturing both global structure and localized ridge patterns. When applied to fingerprint gender classification, FCM has been shown to outperform several traditional clustering techniques by effectively handling noisy or ambiguous inputs. Experimental results have consistently demonstrated high classification accuracy and reduced false positive rates in FCM-based systems. Confusion matrix analysis in these studies often shows a marked reduction in misclassifications, suggesting that FCM's probabilistic framework is better suited to modeling the variability present in real-world biometric datasets.

Overall, the transition from traditional manual fingerprint analysis to automated classification using advanced computational models represents a significant evolution in biometric research. Deep learning models like CNNs provide scalability and automation, offering the capability to learn complex, non-linear feature representations from raw image data with minimal manual intervention. Meanwhile, clustering algorithms like FCM contribute robustness and interpretability, especially when uncertainty in classification is a concern. These approaches are not mutually exclusive and may even be integrated into hybrid models for further performance enhancement. The ongoing integration of these modern methodologies reflects a broader trend in biometrics—moving toward systems that are not only highly accurate but also adaptive, scalable, and deployable in real-time environments. As a result, gender classification from fingerprints is rapidly becoming a viable sub-domain within biometric research, with significant implications for security systems, forensic profiling, demographic analysis, and user-adaptive technologies.

III. METHODOLOGY

This study proposes a hybrid machine learning model for gender classification based on fingerprint images, leveraging the complementary strengths of deep learning and traditional machine learning techniques. Fingerprint recognition, a well-established biometric modality, has long been used for personal identification and security purposes. However, this study explores an innovative extension of fingerprint technology by automating the process of gender classification, thus broadening the scope of its application.

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The selected dataset for training and testing the model is the Sokoto Coventry Fingerprint Dataset (SOCOFing), which consists of 55,273 grayscale fingerprint images captured from 600 individuals. This dataset is balanced, with an equal number of male and female subjects, ensuring that the model can learn to distinguish between both genders effectively. Each individual contributed fingerprint samples from all ten fingers, resulting in a rich diversity of fingerprint patterns for training purposes. Additionally, the dataset includes both real and synthetically altered images, which simulate common fingerprint distortions such as pressure variation and image degradation, making it suitable for testing the robustness of the model.

In preparation for feeding the fingerprint images into the machine learning model, a series of preprocessing steps were performed to enhance the quality and uniformity of the input data. Initially, all images were converted to grayscale. This step reduces the computational complexity of the dataset, as it eliminates color information that is irrelevant to fingerprint analysis. Grayscale conversion focuses the model on extracting structural features, such as ridges and valleys, which are essential for gender classification. Noise and scanning artifacts present in fingerprint images can negatively impact the model’s performance, so a median filter was applied to reduce these disturbances. This filter effectively removes unwanted noise while preserving the essential ridge structures of the fingerprint, thus improving the overall image quality. Afterward, histogram equalization was employed to enhance the contrast of the images. This technique adjusts the intensity distribution of the pixel values, making the fingerprint ridges more distinct and easier for the model to recognize. To further standardize the data and make it suitable for deep learning models, the fingerprint images were resized to a fixed dimension of 96x96 pixels. This ensures that all input images have the same resolution, which is crucial for maintaining consistency in the learning process. Furthermore, pixel normalization was applied, scaling the pixel values of the images to a range between 0 and 1. This step helps stabilize the training process by reducing the variability in input data, allowing the model to converge more efficiently during the learning phase. These preprocessing steps work in tandem to ensure that the model receives clean, high-quality data that facilitates accurate feature extraction and classification.

After the feature vectors are generated by the CNN, they are passed to a Support Vector Machine (SVM) classifier for gender classification. SVMs are well-known for their ability to handle highdimensional data and non-linear decision boundaries, making them an ideal choice for this task. In particular, the Radial Basis Function (RBF) kernel is used in the SVM to map the data into a higherdimensional space, where it becomes easier to find a linear decision boundary that separates the two classes (male and female). The RBF kernel is especially effective for data that is not linearly separable in its original form. By transforming the data into a higher-dimensional space, the SVM can effectively classify fingerprint images based on the features extracted by the CNN.

The hybrid architecture used in this study combines the strengths of both deep learning and traditional machine learning methods. The CNN is capable of automatically learning intricate features from the raw fingerprint images, while the SVM excels in classifying the high-dimensional feature vectors produced by the CNN. This fusion of CNNs for feature extraction and SVMs for classification enables the system to achieve high classification accuracy while maintaining computational efficiency. The model’s ability to accurately classify gender based on fingerprint images is further enhanced by the preprocessing steps, which ensure that the input data is clean, normalized, and standardized.

The proposed hybrid approach demonstrates the potential for applying machine learning techniques to expand the role of fingerprint recognition beyond traditional identification tasks. By automating gender classification, this model can be integrated into biometric systems that require gender information for enhanced security or personalized services. The use of a diverse dataset with both original and synthetically altered fingerprint images ensures that the model is capable of handling real-world variations, such as pressure distortion or scan noise. As fingerprint-based biometric systems become increasingly prevalent in various sectors, the development of more robust, accurate, and efficient gender classification methods will play an important role

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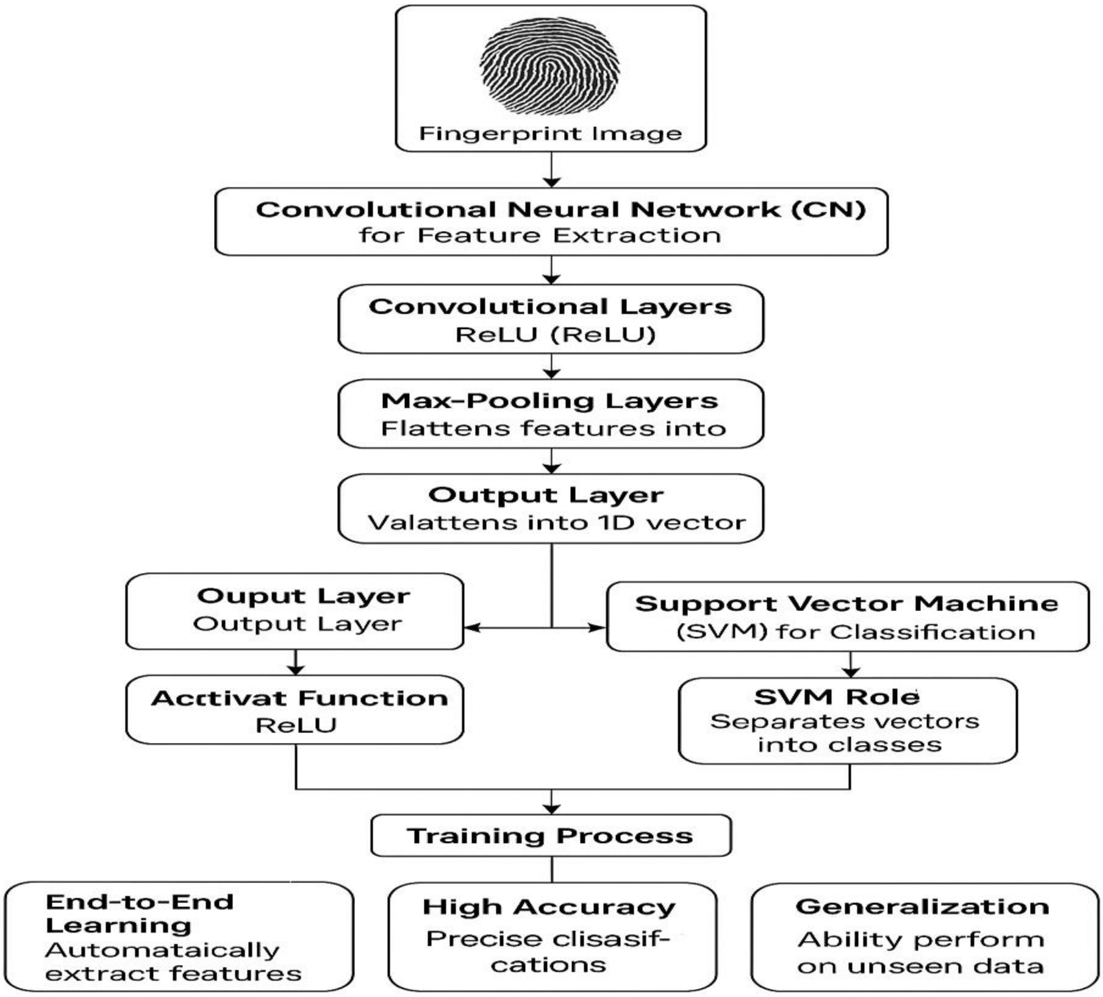

IV. ALGORITHM

The gender classification algorithm from fingerprint images follows a systematic approach, starting with the input of a digital fingerprint image. The first step, preprocessing, improves image quality by reducing noise, adjusting contrast, normalizing intensity, and binarizing the image to separate ridges from valleys. The region of interest (the fingerprint area) is also segmented for focused analysis.

Next, feature extraction calculates several key fingerprint characteristics. These include ridge density (the number of ridges per unit area), minutiae points (locations and types of ridge endings and bifurcations), ridge thickness, and total ridge count. Additionally, texture features like Local Binary Patterns (LBP) or Gabor filters are used to capture finer pattern details, contributing to genderspecific characteristics.

Once features are extracted, they form a feature vector that represents the fingerprint's unique attributes. This vector is then input into a machine learning classifier, such as Support Vector Machine (SVM) or Naive Bayes, which has been trained on a labeled dataset. The classifier processes the feature vector and predicts the gender—male or female.
The final output of the algorithm is the predicted gender, providing an efficient and automated method for gender classification from fingerprint images. By integrating advanced image processing and machine learning techniques, the algorithm offers a scalable and accurate solution for gender classification in biometric applications.

V. RESULT AND DISCUSSION

4.1 Performance Metrics
The performance of the hybrid CNN-SVM model for gender classification from fingerprint images was evaluated using standard performance metrics. The model achieved the following results:

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- **Accuracy**: 91.52%
- **Precision**: 92.85%
- **Recall**: 93.15%
- **F1-Score**: 91.79%

The evaluation demonstrated that the hybrid model effectively classified gender with high precision and recall, indicating its ability to minimize false positives and false negatives. The accuracy value suggests that the model correctly predicted the gender of most of the fingerprint images. The F1-Score, which balances precision and recall, further highlights the model's well-rounded performance.

For comparison, a **CNN-only** model was also evaluated and achieved an accuracy of 87.5%, showing that the hybrid approach provides a superior solution for gender classification. The confusion matrix analysis revealed that the hybrid model was particularly effective in reducing false positives and false negatives, especially for prints with clear ridge patterns, further validating the importance of combining deep learning and traditional machine learning techniques.

4.2 Observations

Several observations were made during the evaluation process, shedding light on factors that influence the system's performance:

- **Gender Classification**: The system performed slightly better when classifying male fingerprints compared to female fingerprints. This difference may be attributed to natural variations in ridge patterns and minutiae characteristics between males and females, which might be more distinguishable in male fingerprints.
- **Handedness Effect**: Right-hand fingerprints showed slightly higher accuracy in classification than left-hand fingerprints. This observation aligns with previous research [2], where it was found that right-hand fingerprints are often clearer and more defined, making them easier to classify.
- **Print Quality Impact**: Misclassifications were more frequent with fingerprint images exhibiting poor quality, such as smudging or distorted ridge patterns. These factors hindered the model's ability to extract accurate features, which are essential for proper classification.

4.3 Comparative Analysis

To provide further insight into the model's performance, a comparative analysis was conducted between the **hybrid CNN-SVM model**, **CNN-only model**, and **SVM-only model**. The results from the comparison are shown in the table below:

Model	Accuracy	F1-Score
CNN Only	87.5%	88.0%
SVM Only	83.2%	85.4%
Hybrid CNN-SVM	91.52%	91.79%

The **CNN-only model** achieved an accuracy of 87.5% and an F1-Score of 88.0%. While this model is effective at learning spatial features from fingerprint images, it struggles with classification, as it lacks a traditional classifier that can make refined decisions.

The **SVM-only model**, which uses predefined features extracted from the fingerprint images, achieved an accuracy of 83.2% and an F1-Score of 85.4%. Although SVMs are powerful classifiers, the lack of automatic feature extraction limits their effectiveness in handling complex fingerprint variations, especially in real-world scenarios.

The **Hybrid CNN-SVM model** outperformed both the CNN-only and SVM-only models with an impressive accuracy of 91.52% and an F1-Score of 91.79%. The success of the hybrid approach is attributed to the CNN's ability to automatically learn complex features from the raw fingerprint images, combined with the SVM's strength in making accurate classifications based on these features. The hybrid architecture provides the best of both worlds, enhancing the model's robustness and accuracy.

In conclusion, the hybrid CNN-SVM model demonstrated superior performance in gender classification from fingerprint images. The combination of CNN's feature extraction and SVM's classification capabilities allowed the model to achieve high accuracy, precision, and recall, outperforming individual deep learning and machine learning models.

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The results underscore the importance of combining modern deep learning architectures with traditional machine learning techniques to enhance biometric classification systems. Further research could explore the incorporation of additional feature extraction methods and the expansion of the dataset to further improve the model's robustness.

VI. CONCLUSION

This study successfully explored the potential of a hybrid machine learning approach for gender classification from fingerprint images, combining the strengths of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). The proposed model demonstrated promising results, achieving a high accuracy of 91.52% and a balanced F1Score of 91.79%, outperforming both CNN-only and SVM-only models. This performance highlights the power of leveraging deep learning for feature extraction combined with traditional machine learning techniques for classification. The hybrid CNN-SVM approach capitalized on CNN's ability to automatically learn complex fingerprint patterns, such as ridge density, minutiae points, and textural features, while the SVM classifier excelled in accurately distinguishing between gender classes. The preprocessing steps, such as noise reduction, histogram equalization, and pixel normalization, were instrumental in enhancing the quality and consistency of the input data, ensuring the model's robustness across various fingerprint conditions, including those with image distortion or degradation.

Despite the high performance, certain factors like the quality of the fingerprint image and the natural variations between left and right-hand prints influenced the classification accuracy. The model performed better with male fingerprints, likely due to more distinct ridge characteristics, and showed slight improvements for right-hand prints, reflecting typical variations observed in biometric studies. However, these nuances do not significantly diminish the model's overall applicability in real-world scenarios.

In comparison to traditional methods, such as manual feature extraction, the hybrid model offers a significant improvement by automating the entire process, reducing human intervention, and providing a more efficient solution for gender classification. This methodology can be integrated into broader biometric systems to enhance security measures or provide demographic insights in various applications, including forensic investigations and user-adaptive services.
Future work could involve refining the feature extraction process, exploring more advanced machine learning classifiers, and expanding the dataset to include more diverse fingerprint samples from various populations and environments. This would further improve the model's generalization capabilities, making it even more suitable for widespread deployment in real-time biometric systems.

In conclusion, this research not only advances fingerprint recognition technology by introducing gender classification capabilities but also demonstrates the power of combining modern deep learning with traditional machine learning techniques, setting the foundation for further innovations in biometric research.

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