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A CNN-Based Approach to Gender Prediction Using Biometric Fingerprint Images

SAMUEL OLUWATAYO OGUNLANA[1], FELIX OLA ARANUWA[2], OLATUNDE DAVID AKINROLABU[3]
[1, 2]*Department of Informatics & Information Systems, Adekunle Ajasin University, Akungba Akoko*
[3]*Department of Data Science, Adekunle Ajasin University, Akungba Akoko*

Abstract- ***This study proposes a convolutional neural network (CNN) based framework for predicting gender from fingerprint images. Gender prediction from biometric data has become an important area of research in security, forensics, and human-computer interaction. Unlike traditional fingerprint systems that focus on identity verification, the proposed model automatically learns discriminative fingerprint features, including ridge density, minutiae distribution, and texture patterns, directly from raw images. A total of 6,000 fingerprint images from the SOCOFing dataset, representing both male and female individuals of Sub-Saharan African origin, were used for model development. The data underwent comprehensive preprocessing, including labeling, normalization, enhancement, and segmentation, before being partitioned into training (70%), validation (10%), and testing (20%) subsets. Experimental results demonstrate that the CNN model achieves an overall accuracy of 95%, with precision and recall exceeding 93% for both male and female classes. The area under the ROC curve (AUC) was 0.97 for males and 0.96 for females, indicating excellent discriminative ability. These findings highlight the effectiveness of deep learning for automated gender prediction from fingerprints and suggest its potential applications in biometric authentication, forensic analysis, security, and personalized services. The proposed framework eliminates the challenges of conventional feature engineering and provides a robust, scalable, and accurate solution for gender classification using fingerprint biometrics.***

Keywords-- Biometrics, Gender prediction, fingerprint, CNN.

I. INTRODUCTION

Biometrics is referred to as the science and technology of identifying or verifying individuals based on their unique biological and behavioral characteristics [1] [2]. These human characteristics or traits are distinctive, measurable and naturally endowed features used to label and describe individual [3]. The technology has been adjudged the most practical means of identifying and authenticating individuals in a reliable and fast way through unique physiological and behavioral features [4]. According to [5], biometric characteristics are broadly classified into two major categories: physiological characteristics and behavioral, characteristics. Physiological characteristics are physical attributes that are biologically inherent in the human body. These traits are generally stable and permanent, making them highly reliable for identification purposes [6]. Physiological characteristics can further be divided into morphological and biological traits. Morphological traits relate to the external structure and shape of the human body and include features such as the face, fingerprint, iris, ear shape, palm print, and retinal patterns. These traits are widely adopted in biometric systems due to their uniqueness, ease of acquisition, and high recognition accuracy [7]. Biological traits, on the other hand, are derived from internal biological substances and processes within the human body. Examples include deoxyribonucleic acid (DNA), blood, saliva, odour or scent, and urine. Among these, DNA is regarded as the most distinctive biometric identifier because of its extremely high level of uniqueness. However, despite its accuracy, DNA-based biometric systems are often unsuitable for real-time applications due to high costs, longer processing times, and ethical concerns. As a result, biological biometrics are more commonly used in forensic and criminal investigations rather than everyday authentication systems [8].

Behavioural characteristics in the other way refer to traits that are related to the behaviour or actions of an individual rather than physical attributes. These characteristics are developed over time and reflect how a person performs specific activities. Behavioural

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biometric traits include signature dynamics, handwriting and typing rhythm (keystroke dynamics), voice patterns, gait, walking style, and mouse movement behaviour [9]. While behavioural traits may be influenced by emotional state, health condition, or environmental factors, they offer advantages such as non-intrusive data collection and suitability for continuous authentication systems [1] [10] [11]. Figure 1 depicts generic biometrics characteristics.

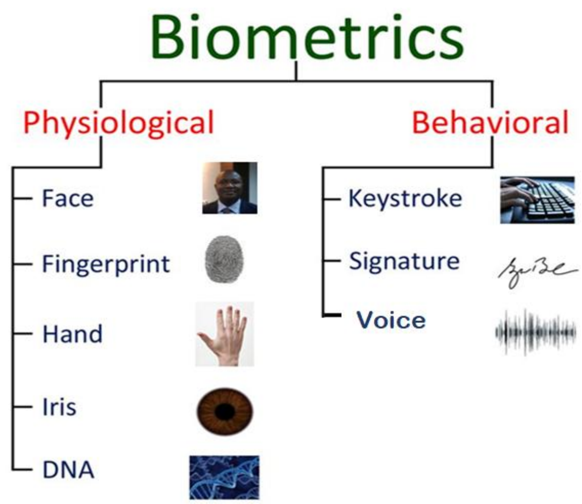

Figure 1: Biometric Characteristics

According to [12], human biometric characteristics are unique, measurable, and capable of distinguishing one individual from another, thereby serving as reliable identifiers. Key areas of biometric application include: security and access control, banking and financial services, law enforcement and forensics investigations. Other areas include healthcare systems, national identity and civil registration, border control and immigration, workplace time and attendance management, and so on. Conventional security mechanisms such as passwords, personal identification numbers (PINs), and identity cards suffer from several limitations, including forgetfulness, theft, duplication, and unauthorized sharing. However, biometric technologies have proffer solution to these challenges by relying on intrinsic personal attributes that cannot easily be transferred or replicated. Consequently, biometrics has been widely recognized as one of the most practical and effective approaches for fast, accurate, and dependable identification and authentication of individuals [1].

In a typical biometric system, biometric data are captured using sensors, processed to extract distinctive features, and compared with stored templates in a database to verify or identify an individual. Figure 2 depict the general architecture of biometrics system.

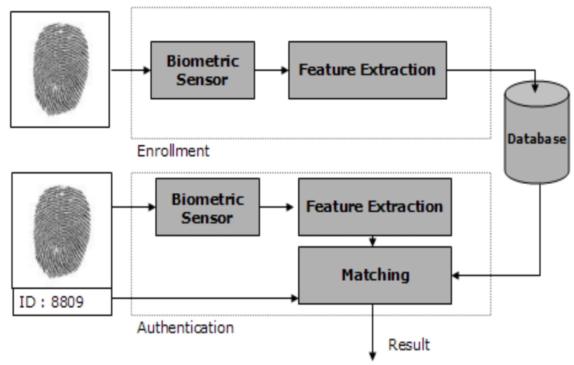

Figure 2: General Architecture of Biometric Systems [13].

For the purpose of this study, fingerprint biometric is considered. The choice of choosing fingerprint biometrics in this study is informed by their uniqueness, permanence, universality, and relative ease of acquisition compared to other biometric traits. According to [9], fingerprint is consists of distinctive pattern formed by ridges and valleys, where ridges represent the raised, dark regions and valleys correspond to the lower, lighter regions The individuality of fingerprints is determined by their overall pattern type, local ridge features, and singular points, commonly referred to as the core and delta. Key fingerprint features, known as minutiae, include ridge endings (terminators), bifurcations, lakes or enclosures, short or independent ridges (islands), spurs, and crossovers. In addition, fingerprint ridges are organized into six primary pattern types: arch, tented arch, left loop, right loop, twin loop, and whorl [14] [15 [16]. These structural characteristics collectively contribute to the distinctiveness of fingerprints and form the basis for biometric analysis. Major fingerprint pattern types are illustrated in Figure 3.

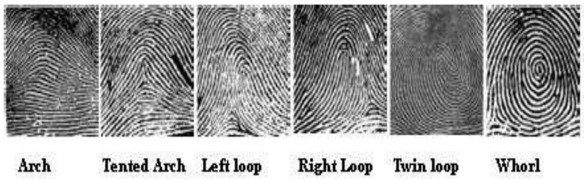

Figure 3: Types of Fingerprint Patterns [15]

Fingerprint-based gender prediction is very valuable in forensic and criminal investigations, where partial or low-quality fingerprint impressions are often encountered. In such scenarios, gender inference from fingerprints can provide crucial demographic cues that can assist law enforcement agencies in narrowing down suspect pools when identity information is unavailable or incomplete [17] [18]. Its process involves the automatic determination of an individual's gender using distinctive patterns present in fingerprint images. Unlike traditional biometric systems that focus solely on identity recognition, fingerprint-based gender prediction exploits subtle ridge characteristics such as ridge density, ridge thickness, minutiae distribution, and texture patterns, which have been shown to exhibit statistically significant differences between male and female fingerprints [17] [19].

According to [20], gender prediction has shifted from traditional manual and subjective methods to technologically driven and automated models that leverage biometric data and machine learning techniques for improved accuracy, reliability, and efficiency. Previous studies have established the existence of significant morphological differences in fingerprint characteristics between genders. These differences include variations in ridge density, with female fingerprints generally exhibiting higher ridge density, while male fingerprints tend to have lower ridge density. Additionally, ridge thickness, minutiae distribution, and ridge count differ across genders, as male fingerprints typically contain fewer ridges within the same fingerprint area. Subtle gender-based variations have also been observed in fingerprint pattern types such as loops, whorls, and arches as well as in the distribution of core and delta points [21]. This study focuses on developing a CNN-based fingerprint gender prediction system that leverages the inherent morphological features of fingerprints to automatically classify gender, addressing the limitations of traditional and earlier computational approaches.

II. OVERVIEW OF CONVOLUTIONAL NEURAL NETWORKS (CNNS)

Convolutional Neural Networks (CNNs) are a specialized class of deep learning models designed to automatically learn hierarchical feature representations from grid-structured data such as images and videos [22] [23]. CNNs have become the dominant approach in computer vision due to their ability to effectively capture spatial patterns and visual structures within data. They have demonstrated outstanding performance across a wide range of applications, including image classification, object detection, facial recognition, medical image analysis, and biometric systems such as fingerprint recognition, iris recognition, and gender prediction [24]. In addition, CNNs represent a powerful and efficient deep learning framework for image and pattern recognition tasks. Their biologically inspired design, combined with advances in computing power and large-scale datasets, has positioned CNNs as a foundational technology in modern artificial intelligence and computer vision research.

The architecture of CNNs is inspired by the organization and functioning of the human visual cortex, where neurons respond selectively to specific regions of the visual field. In biological vision systems, different neurons specialize in detecting simple features such as edges, orientations, and textures, which are progressively combined to recognize complex objects. Similarly, CNNs employ multiple layers to learn low-level features in early layers and higher-level semantic representations in deeper layers [24]. Unlike traditional fully connected neural networks, CNNs exploit two key principles: local connectivity and parameter sharing. Local connectivity allows neurons in a convolutional layer to process only a small receptive field of the input image rather than the entire image. This enables the network to capture spatially local patterns such as edges and corners. Parameter sharing, achieved through convolutional filters, ensures that the same set of weights is applied across different spatial locations in the image. These principles significantly reduce the number of trainable parameters, making CNNs computationally efficient and less prone to overfitting when compared to fully connected architectures [22].

A typical CNN architecture consists of several core components: convolutional layers, activation functions, pooling layers, and fully connected layers. Convolutional layers perform feature extraction by applying learnable filters to the input data. Activation functions such as the Rectified Linear Unit (ReLU) introduce non-linearity, enabling the network to learn complex patterns. Pooling layers, such as max pooling or average pooling, reduce the spatial dimensions of feature maps, thereby lowering computational complexity and improving robustness to spatial variations. Fully connected layers, usually placed near the output, perform high-level reasoning and classification based on the extracted features [25]. Figure 4 depicts a typical CNN architecture.

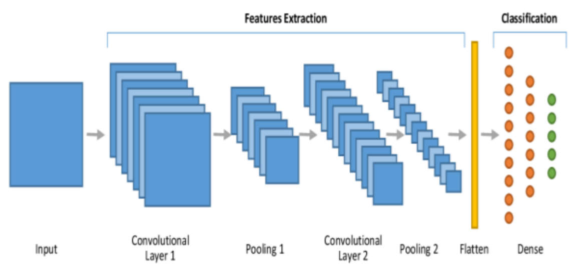

Figure 4: Architecture of CNN (Fully Connected Layers) [25]

The convolutional layer is the fundamental building block of a CNN. It applies a set of learnable filters (kernels) that slide across the input image to extract local features such as edges, corners, ridges, and textures.

Mathematically, the convolution operation can be expressed as:

$$(F * I)(x, y) = \sum_{i} \sum_{j} I(x+i, y+j) \cdot F(i, j) \tag{1}$$

Where I represents the input image and F denotes the filter.

In biometric applications, convolutional layers are effective in learning ridge patterns, minutiae distributions, and texture features particularly from fingerprint images.

After convolution, an activation function introduces non-linearity into the network. The most commonly used activation function in CNNs is the Rectified Linear Unit (ReLU):

$$f(x) = \max(0, x) \tag{2}$$

ReLU improves training efficiency by reducing vanishing gradient problems and accelerating convergence.

The pooling layers reduce the spatial dimensions of feature maps while retaining important information. This helps in reducing computational cost, preventing overfitting and achieving translation invariance. Common pooling techniques include max pooling and average pooling. In fingerprint analysis, pooling ensures robustness against small distortions and noise. The fully connected layers appear toward the end of the CNN architecture. They take the flattened feature maps and perform high-level reasoning for classification or prediction tasks. In gender prediction systems, the fully connected layer maps extracted fingerprint features to gender classes (male/female). The output layer produces the final prediction. For binary classification problems such as gender prediction, a sigmoid or softmax activation function is commonly used. CNNs have proven particularly effective in biometric and image-based security systems because of their ability to learn discriminative features automatically without the need for handcrafted feature extraction. In biometric applications such as fingerprint recognition, face recognition, and medical imaging, CNNs outperform traditional machine learning methods by achieving higher accuracy and robustness under varying conditions such as noise, illumination changes, and occlusions [23]. Their adaptability and scalability have also led to widespread adoption in real-world systems, including mobile devices, surveillance systems, and healthcare diagnostics.

Several studies have explored different approaches for leveraging fingerprint features to predict gender, ranging from traditional statistical and morphological analyses to contemporary machine learning and deep learning techniques. These studies collectively demonstrate a progressive evolution in methodology, moving from handcrafted feature engineering to automated feature learning using convolutional neural networks (CNNs). Early research primarily concentrated on the morphological and statistical properties of fingerprints.

Morphological fingerprint characteristics, such as ridge patterns and minutiae types, were hypothesized to exhibit gender-specific differences. [26] conducted an analysis of fingerprint pattern distributions and observed significant gender-related variations, noting that whorl patterns are more prevalent in male fingerprints, whereas loop patterns occur more frequently in female fingerprints. This observation suggested that global fingerprint pattern types could serve as discriminatory markers for gender prediction. In a complementary study [27]. examined additional fingerprint attributes, including ridge count, ridge density, and fingertip dimensions. Their findings indicated that ridge density serves as a key discriminative feature, with female fingerprints generally exhibiting higher ridge density compared to male fingerprints. These early studies underscored the potential of fingerprint features for gender classification, yet they were largely dependent on statistical measurements and handcrafted descriptors.
To improve classification performance, researchers incorporated signal processing techniques alongside traditional feature extraction methods. One commonly adopted approach combined discrete wavelet transform (DWT) with singular value decomposition (SVD) to capture both texture and frequency-domain information from fingerprint images [28]. This approach was often paired with k-nearest neighbor (k-NN) classifiers, which classify fingerprints based on proximity in feature space. Studies employing this methodology reported classification accuracies ranging from 80% to 88%, demonstrating the feasibility of fingerprint-based gender prediction. However, these methods had several limitations, they were highly sensitive to noise, required extensive preprocessing, and relied heavily on expert knowledge for feature selection, which limited their scalability and generalizability to large or diverse datasets.

With the advent of machine learning, researchers increasingly adopted supervised classifiers to enhance predictive performance. Techniques such as multilayer perceptrons (MLP), support vector machines (SVM), and random forest classifiers were applied to wavelet-or texture-based fingerprint features. For instance, [29] used wavelet-derived features in conjunction with an MLP classifier and reported an accuracy of approximately 80% on standard fingerprint datasets. Similarly, fuzzy clustering and ensemble learning techniques were explored to handle variability and uncertainty in fingerprint features [30].

While these approaches improved robustness, they also introduced higher computational complexity and continued to depend on manually engineered features, which constrained adaptability to new datasets.

The emergence of deep learning, particularly convolutional neural networks (CNNs), has transformed fingerprint-based gender prediction by enabling automated feature extraction directly from raw images. CNNs are capable of learning hierarchical feature representations, capturing both low-level textures and high-level semantic patterns, without requiring handcrafted descriptors [24]. Some studies have expanded fingerprint-based gender prediction into broader soft biometric frameworks, integrating gender classification with attributes such as ethnicity or age. Such approaches enable richer biometric profiling, which can be applied in forensic investigations, security systems, and identity management [31]. In spite of these advancements, several challenges persist, many fingerprint datasets remain imbalanced, with disproportionate representation of male and female samples, which causes bias model performance, limited generalization across diverse populations and variations in fingerprint quality also pose significant challenges for practical deployment. Furthermore, the computational requirements of deep learning models, particularly in resource-constrained environments, highlight the need for optimized architectures and efficient inference methods. Addressing these issues is crucial for improving the reliability and

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applicability of fingerprint-based gender prediction systems in real-world contexts.

III METHODOLOGY

This current study developed a convolutional neural network (CNN) based model for gender prediction using fingerprint biometric images. The architecture of the model is presented in Figure 5.

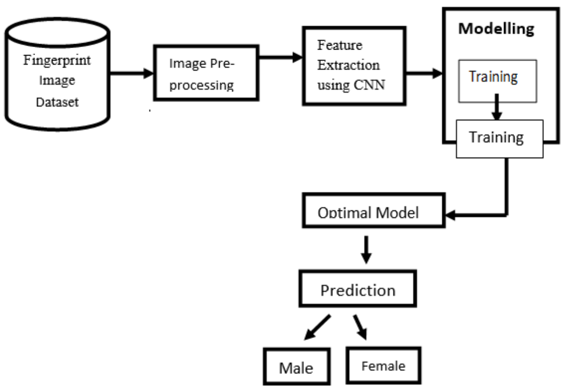

Figure 5: The Conceptual Model for the Gender Prediction

Figure 6 shows the CNN architecture for the fingerprint feature extraction.

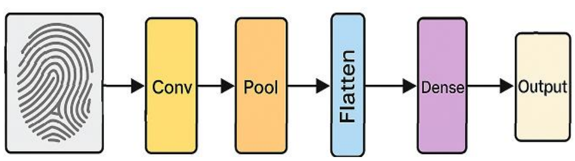

Figure 6: The CNN Architecture for Fingerprint Feature Extraction

The approach involves data acquisition, preprocessing, model development, training, testing, and performance evaluation to determine the effectiveness of CNNs in predicting gender from fingerprint patterns.

3.1 Data Acquisition and Preprocessing

The fingerprint dataset used in this study were obtained from the Sokoto Coventry Fingerprint (SOCOFing) dataset. SOCOFing is a biometric fingerprint database designed for academic research purposes. The dataset contains 6,000 fingerprint images from 600 African subjects with unique attributes such as labels for genders (male and female), hand and finger name.

The dataset provides high-resolution grayscale fingerprint images, balanced representation of both genders and variations in fingerprint patterns and quality. These characteristics make the dataset suitable for evaluating fingerprint-based gender prediction models. Figure 7 shows the sample image of the dataset collected.

To enhance image quality and ensure reliable feature learning, several preprocessing steps were applied:

a. Each fingerprint image was properly labeled according to the associated gender class (male or female), ensuring consistency and correctness in supervised learning.
b. Image normalization was performed to standardize grayscale intensity values across all fingerprint images. This step reduces illumination and pressure variations caused by sensor differences during fingerprint acquisition.
c. Fingerprint images were enhanced to improve ridge valley contrast using filtering techniques. This process strengthens ridge clarity and suppresses background noise, facilitating better feature extraction by the CNN.

Segmentation was applied to isolate the region of interest (ROI) containing the fingerprint pattern from the background. This ensures that the CNN focuses only on relevant fingerprint information during training.

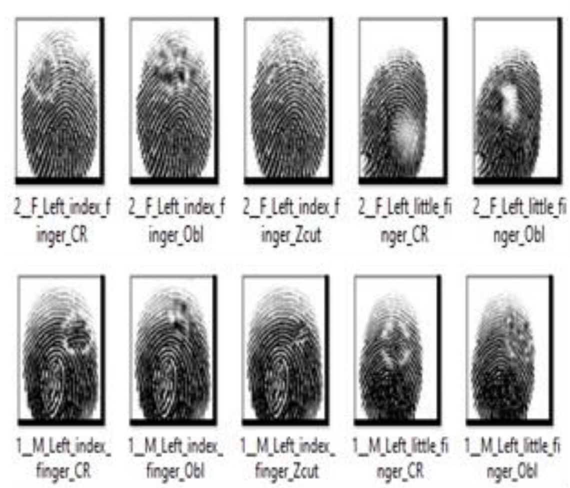

Figure 7: Samples of Fingerprint Images: (https://www.kaggle.com/ruizgara/socofing)

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The CNN was designed to automatically learn discriminative fingerprint features relevant for gender prediction. Multiple convolutional layers were employed to extract low-level and high-level features such as ridge orientation, texture, and spatial patterns from fingerprint images. The Rectified Linear Unit (ReLU) activation function was used to introduce non-linearity and accelerate convergence during training. Max-pooling layers were applied after convolutional layers to reduce spatial dimensionality, minimize computational cost, and enhance robustness to minor distortions and noise. Flattened feature maps were passed to fully connected layers, which performed high-level reasoning and learned decision boundaries between gender classes. The output layer consisted of two neurons representing the male and female classes, with a softmax activation function used to generate class probabilities.

The preprocessed dataset was divided into three subsets to support model development and evaluation: 70% of the dataset was devoted for training, 20% of the dataset for testing and 10% of the dataset for validation. The training set was used to learn model parameters; the validation set was employed for hyperparameter tuning and overfitting control, while the testing set was reserved for final performance evaluation. The CNN model was trained using supervised learning. During the training, cross-entropy loss was used as the objective function, Adam optimizer was employed for weight optimization and batch learning was applied to improve stability and convergence. Training was performed iteratively until optimal performance was achieved on the validation dataset. All experiments were conducted using a standard deep learning framework (e.g., TensorFlow or PyTorch) on a computer system equipped with sufficient processing power and memory to support CNN training and evaluation.

IV RESULTS AND DISCUSSION

Experimental results demonstrate that the CNN model achieves an overall accuracy of 95%, with precision and recall exceeding 93% for both male and female classes. The area under the ROC curve (AUC) was 0.97 for males and 0.96 for females, indicating excellent discriminative ability. These findings highlight the effectiveness of deep learning for automated gender prediction from fingerprints and suggest its potential applications in biometric authentication, forensic analysis, security, and personalized services.

4.1 Performance Metrics

The performance of the proposed CNN-based gender prediction model was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix. The evaluation was conducted on the test set, which comprised 1,200 fingerprint images (20% of the total 6,000 images), while the validation set (600 images) was used for hyperparameter tuning during training.

The standard metrics were computed as follows:

Accuracy – Overall proportion of correctly classified samples:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{582+558}{600+600} = \frac{1140}{1200} = 0.95\ (95\%) \quad (3)$$

Precision – Proportion of predicted positives that are correct:

$$\text{Precision}_{male} = \frac{TP}{TP+FP} = \frac{582}{582+42} \approx 0.933\ (93.3\%)$$

$$\text{Precision}_{female} = \frac{TP}{TP+FP} = \frac{558}{558+18} \approx 0.969\ (96.9\%) \quad (4)$$

The confusion matrix in Figure 8 summarizes the classes model's classification performance across the male and female:

Recall (Sensitivity) – Proportion of actual positives correctly identified:

Recall (Sensitivity) – Proportion of actual positives correctly identified:

$$\text{Recall}_{male} = \frac{TP}{TP+FN} = \frac{582}{582+18} \approx 0.97\ (97\%)$$

$$\text{Recall}_{female} = \frac{TP}{TP+FN} = \frac{558}{558+42} \approx 0.93\ (93\%) \quad (5)$$

F1-Score – Harmonic mean of precision and recall:

$$F1_{male} = 2 \cdot \frac{0.933 \cdot 0.97}{0.933 + 0.97} \approx 0.951\ (95.1\%)$$

$$F1_{female} = 2 \cdot \frac{0.969 \cdot 0.93}{0.969 + 0.93} \approx 0.949\ (94.9\%) \quad (6)$$

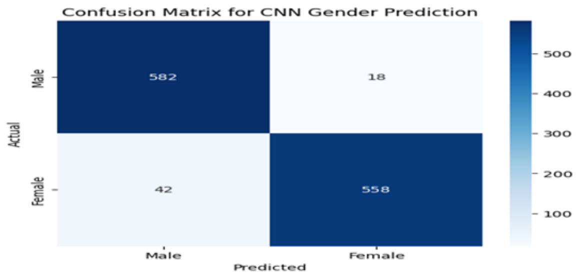

Figure 8: The Confusion Matrix for CNN Gender Prediction

By interpretation, 582 out of 600 male fingerprints were correctly classified. 558 out of 600 female fingerprints were correctly classified. The misclassifications were relatively low (3% for male, 7% for female).

The Receiver Operating Characteristic (ROC) curve was plotted for both male and female classes, and the Area Under the Curve (AUC) values were computed as depicted in Figure 9:

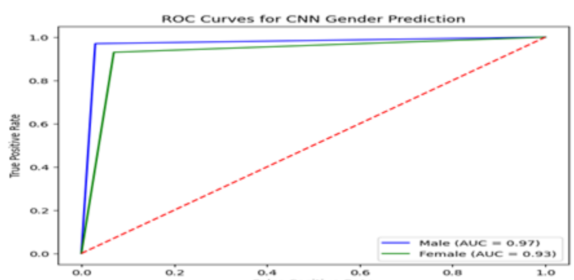

Figure 9: The ROC Curves for CNN Gender Prediction

The AUC value is very close to 1 indicating excellent discriminative ability of the CNN model for both genders. Table 1 and Table 2 show the summary of the model performance and comparison with the benchmark respectively.

Table 1: Summary of Model Performance

Metric	Male	Female
Accuracy	95%	95%
Precision	93.3%	96.9%
Recall	97%	93%
F1-Score	95.1%	94.9%
AUC	0.97	0.96

The CNN model demonstrates high accuracy and balanced performance across both male and female classes. The results indicate that the proposed model can reliably predict gender from fingerprint images with minimal misclassification, outperforming traditional machine learning methods that rely on handcrafted features

Table 2: Comparison of prediction performance of current work with benchmark work for this study

Author	Model	Dataset	gender	Precision	recall	F1-Score	Accuracy
Oladele M. O. et.al., (2022)	CNN	SOCOFing	Female Male	72% 71%	70% 73%	71% 72%	72%
Current research	CNN	SOCOFing	Female Male	96.7% 93.3%	93% 97%	94.9% 95.1%	95%

IV. CONCLUSION

This study presented a Convolutional Neural Network (CNN) based approach for gender prediction using fingerprint biometrics, demonstrating the effectiveness of deep learning in capturing discriminative features from raw fingerprint images. The proposed methodology integrated comprehensive data preprocessing steps, including labeling, normalization, enhancement, and segmentation, to improve image quality and facilitate robust feature extraction. Using the SOCOFing dataset of 6,000 fingerprint images, the dataset was partitioned into training, validation, and testing subsets, and the CNN model was trained to automatically learn gender-specific patterns such as ridge density, minutiae distribution, and texture characteristics. Experimental results indicate that the proposed CNN model achieves high predictive performance, with an overall accuracy of 95%, balanced precision and recall across male and female classes, and AUC values exceeding 0.95. These findings demonstrate that deep learning models can outperform traditional feature-based or classical machine learning approaches that rely on handcrafted features and extensive preprocessing. The confusion matrix and ROC curves further confirm the robustness of the model in correctly classifying fingerprint images with minimal misclassification. The outcomes of this research highlight the potential of fingerprint-based gender prediction in applications such as forensic identification, biometric authentication, security, and human-computer interaction. The use of CNNs proffers solution to the challenges of conventional feature engineering and offers resilience to noise, illumination variations, and fingerprint quality inconsistencies. This work establishes a reliable, automated, and scalable framework for gender prediction from fingerprints, providing a foundation for future research that could incorporate larger, more diverse datasets, hybrid deep learning architectures, and additional soft biometric traits to further enhance performance and applicability in real-world biometric systems.

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