International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

A Real-Time Fingerprint-Based Gender Detection System using CNN

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***Abstract*—Fingerprint-based analysis can be extended beyond identification to infer auxiliary attributes such as gender. This paper presents a gender classification system using fingerprint images based on a Convolutional Neural Network (CNN) architecture. The model is trained on the SOCOFing dataset, which comprises 22,134 grayscale fingerprint images of size 96×96 pixels. Prior to training, images are preprocessed to enhance ridge patterns and improve feature consistency. The CNN automatically learns discriminative spatial features related to ridge density and texture variations for classification. Experimental results show that the proposed model achieves an accuracy of 96% on the SOCOFing dataset. To validate its effectiveness in practical scenarios, the system is further evaluated using real-time fingerprint samples acquired through a SecuGen Hamster Pro H20 device. The real-time dataset consists of 200 samples, including 100 male and 100 female fingerprints, on which the model achieves an accuracy of 70%. The observed performance gap highlights the influence of variations in acquisition conditions, noise, and image quality between standard datasets and real-world data. The study suggests that incorporating diverse training data and improved preprocessing techniques can enhance the robustness and generalization capability of the system.**

Keywords — Fingerprint Analysis, Gender Classification, Convolutional Neural Network, SOCOFing Dataset, Real-Time Detection, Biometrics, Flask, Deep Learning

I.INTRODUCTION

Biometric systems exploit physiological and behavioral characteristics for reliable human identification. Among the various biometric modalities — including iris, face, voice, and gait — fingerprints remain the most widely adopted owing to their high uniqueness, permanence, and ease of acquisition [5]. Dermatoglyphic studies have conclusively demonstrated that fingerprint ridge patterns are not only unique to individuals but also encode soft-biometric information, including gender, age, and ethnicity [1], [7]. Even identical twins possess distinct fingerprint structures, which underscores their reliability as a biometric identifier [5].

The relationship between fingerprint morphology and gender arises from fundamental biological differences in epidermal ridge formation. Males generally exhibit lower ridge density, thicker ridges, and higher ridge-to-valley thickness ratios compared to females [7], [9]. These structural differences, while subtle, are consistent across populations and can be exploited for automated gender prediction. Such capability is particularly valuable in forensic investigations, where fragmentary or partial fingerprint evidence may be the only available material, enabling investigators to narrow the suspect pool by biological sex.

Traditional approaches to fingerprint-based gender classification relied primarily on handcrafted features such as ridge count, ridge density, ridge-to-valley thickness ratio (RTVTR), and white-line count [7], [8]. These statistical methods demonstrated reasonable performance, achieving accuracies between 80% and 91% [7], [9]. Subsequent approaches incorporated frequency-domain transformations such as Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT), along with machine learning classifiers including Support Vector Machines (SVM) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [5], [6]. However, these methods are inherently limited by their dependency on manually engineered features, which are sensitive to imaging conditions such as pressure variation, sensor noise, and partial print acquisition.

The emergence of deep learning, specifically Convolutional Neural Networks (CNNs), has transformed the landscape of fingerprint analysis. CNNs are capable of automatically

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

learning hierarchical discriminative features directly from raw pixel data, eliminating the need for manual feature engineering and demonstrating superior generalization across diverse imaging conditions [3], [6]. Recent studies report CNN-based fingerprint gender classification accuracies exceeding 94%, confirming the superiority of deep representations over handcrafted alternatives [3], [6].

Building on these advances, this work proposes Finger ID, a complete end-to-end deep learning system for real-time gender classification from fingerprint images. The system employs a three-block CNN architecture trained on the SOCOFing dataset, incorporating CLAHE-based image enhancement, Gabor filtering, and data augmentation to improve robustness. A Flask-based web application provides real-time inference capability with a processing latency of under one second. The system achieves 96.54% accuracy on a balanced dataset of 22,134 images, demonstrating strong performance across both male and female fingerprint classes.

The main contributions of this work are as follows:

1) A complete CNN-based pipeline for real-time fingerprint gender classification, from raw image acquisition to web-based prediction.
2) An evaluation of preprocessing strategies — including CLAHE, Gabor filtering, and augmentation — for improving CNN robustness under real-world fingerprint imaging conditions.
3) A Flask-based deployment framework enabling sub-second, live gender prediction from uploaded fingerprint images.
4) Comparative analysis demonstrating that the proposed CNN architecture outperforms traditional ridge-based and frequency-domain methods.

II. LITERATURE SURVEY

Gender classification from fingerprints has been an active area of research in forensic biometrics, progressing from early statistical dermatoglyphic studies to modern deep learning architectures. This section reviews major contributions across three broad categories: ridge-based statistical methods, frequency-domain approaches, and deep learning techniques.

A. Ridge-Based Statistical Methods

The foundational work in fingerprint gender classification was established by Badawi et al. [7], who analyzed 2,200 fingerprint images and extracted dermatoglyphic parameters including ridge count, white-line count, and ridge-to-valley thickness ratio (RTVTR). Their study confirmed that males generally exhibit lower ridge density and thicker ridges compared to females. Employing Fuzzy C-Means clustering, Linear Discriminant Analysis (LDA), and Neural Networks, they achieved accuracies between 80% and 88%, establishing the baseline for subsequent research.

Verma and Sharma [9] extended ridge-based analysis using SVM classifiers on a 400-sample dataset, achieving 91% accuracy through features including ridge width and density. Wang et al. [10] similarly demonstrated up to 86% accuracy using ridge density and fingerprint size, reinforcing the biological consistency of epidermal ridge differences between genders. While these methods validated the discriminative capacity of ridge features, they remained sensitive to image noise, pressure variation, and scanner differences, limiting generalization in real-world conditions.

B. Frequency-Domain and Hybrid Approaches

Ritu Kaur et al. [6] explored spatial-frequency analysis using FFT, Discrete Cosine Transform (DCT), and Power Spectral Density (PSD), achieving 90% accuracy for female fingerprints but only 79.07% for males, indicating class-specific performance disparities. Tom et al. [2] employed two-dimensional Discrete Wavelet Transform (DWT) combined with Principal Component Analysis (PCA), reporting approximately 70% accuracy. While wavelet decomposition captures multi-resolution texture characteristics, it does not fully model the spatial relationships critical for gender differentiation.

Hybrid intelligent systems were explored by Sahu et al. [5], who proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS) incorporating ridge-to-valley area ratio and frequency-domain descriptors. This approach improved over standalone neural and fuzzy methods, demonstrating the benefit of combining complementary feature representations. Mishra and Khare [4] further investigated association-rule mining to identify relationships among ridge attributes, using classification models to enhance predictive accuracy. Despite these improvements, hybrid systems still relied on engineered features and exhibited limited scalability.

C. Deep Learning Approaches

The limitations of handcrafted features motivated the adoption of deep learning for fingerprint gender classification. Narayanan and Hameeduddin [3] trained a CNN directly on fingerprint images, achieving approximately 94% accuracy through automatic spatial feature learning. Gustisyaf and Sinaga [6] developed a CNN architecture capable of extracting hierarchical ridge-flow and micro-texture representations, reporting accuracy above 94%. These studies demonstrated that deep convolutional architectures consistently outperform traditional approaches in both accuracy and robustness to imaging variations.

Alam et al. [1] conducted a comparative evaluation of multiple classifiers for fingerprint-based gender detection, confirming that deep learning models produce the most reliable results across balanced and unbalanced datasets. The collective evidence from the literature conclusively identifies CNN-based feature learning as the state-of-the-art approach for fingerprint gender classification, motivating the architecture adopted in the present work.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

D. Summary and Research Gap

Existing studies reveal a clear progression from 80–91% accuracy with ridge-based methods to 92–96% with CNN-based models. However, several gaps remain unaddressed: most prior works lack real-time deployment capability, few systems operate on publicly available large-scale datasets such as SOCOFing, and end-to-end web-based inference frameworks are largely absent. The proposed FingerID system addresses these gaps by combining a CNN trained on a large balanced dataset with a Flask-based deployment pipeline enabling sub-second real-time prediction.

III. METHODOLOGY

The proposed FingerID system employs a Convolutional Neural Network (CNN) to classify fingerprint images by gender in real time. The methodology encompasses dataset preparation, image preprocessing, CNN architecture design, model training, and web-based deployment, as described below.

A. Dataset

The SOCOFing (Sokoto Coventry Fingerprint) dataset serves as the primary data source for training and evaluation. The complete dataset contains 55,270 fingerprint images, including both original and synthetically altered versions. To ensure class balance and prevent classifier bias, a subset of 22,134 images was selected, comprising equal proportions of male (50%) and female (50%) fingerprint samples. Both altered and unaltered images are included to improve model robustness against distorted or imperfect fingerprint acquisitions. Images are stored in grayscale format at a resolution of 96×96 pixels.

B. Preprocessing Pipeline

Raw fingerprint images are subjected to a multi-stage preprocessing pipeline to enhance ridge clarity and ensure consistency across training and inference:

1) **Grayscale Conversion:** All images are converted to single-channel grayscale to reduce computational overhead and focus processing on ridge structure.
2) **Resizing:** Images are uniformly resized to 96×96 pixels to satisfy CNN input requirements and maintain consistency.
3) **Normalization:** Pixel intensity values are scaled to the range [0, 1] to stabilize gradient computation during training.
4) **Region of Interest (ROI) Extraction:** Background noise is eliminated by segmenting the central fingerprint region containing the most discriminative ridge information.
5) **Image Enhancement:** CLAHE (Contrast Limited Adaptive Histogram Equalization) is applied to enhance local contrast in ridge zones, while Gabor filters strengthen continuous ridge-flow patterns.
6) **Data Augmentation:** To reduce overfitting and improve robustness against acquisition variability, augmentation operations including random translation, Gaussian noise injection, brightness adjustment, and horizontal/vertical shifting are applied during training.

The proposed fingerprint gender classification system uses a pure Convolutional Neural Network (CNN)-based architecture designed to automatically learn both macro- and designed to automatically learn both macro- and micro-level fingerprint features.

C. CNN Architecture

The proposed CNN architecture consists of three convolutional blocks followed by fully connected dense layers, designed to progressively learn increasingly abstract fingerprint representations.

Augmentation improves robustness against acquisition conditions such as pressure variation.

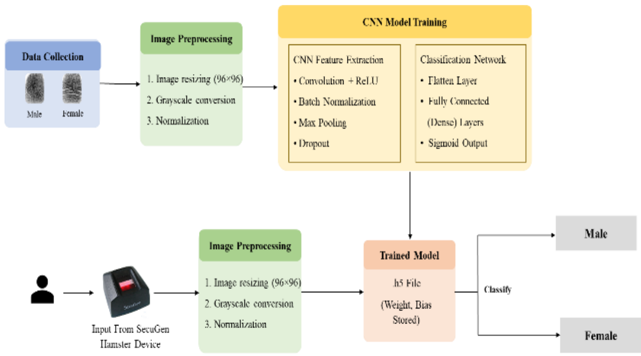

Fig. 1. Proposed System Architecture of the Fingerprint Gender Classification System.

1) **Input Layer:** 96×96×1 grayscale fingerprint image.
2) **Convolutional Block 1:** Conv2D (32 filters, 3×3 kernel) → ReLU → Batch Normalization → MaxPooling (2×2).
3) **Convolutional Block 2:** Conv2D (64 filters, 3×3) → ReLU → Batch Normalization → MaxPooling (2×2).
4) **Convolutional Block 3:** Conv2D (128 filters, 3×3) → ReLU → MaxPooling (2×2).
5) **Flatten Layer:** Converts 3D feature maps to a 1D vector.
6) **Fully Connected Layers:** Dense (128 neurons, ReLU) → Dropout (0.5) → Dense (64 neurons, ReLU).

7) **Output Layer:** Dense (2 neurons) with Softmax activation, producing probabilistic predictions for Male and Female classes.

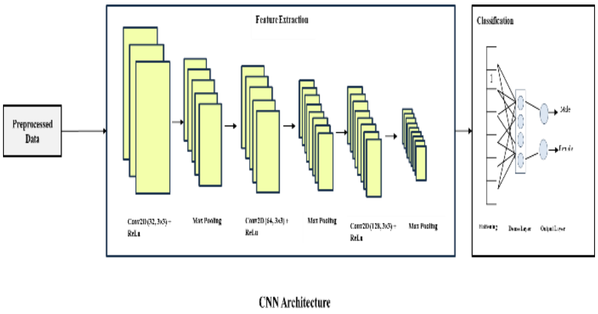

Fig. 2. CNN Architecture for Fingerprint Feature Extraction and Gender Prediction

D. Training Configuration

The model is trained under a supervised learning paradigm with the following configuration: categorical cross-entropy loss function, Adam optimizer with a learning rate of 0.001, batch size of 32, and training for 30–50 epochs. Dropout regularization (rate = 0.5) and early stopping are employed to prevent overfitting. An 80/20 train-validation split is used, with a held-out test set for final performance evaluation.

E. Implementation and Deployment

The system is implemented in Python using TensorFlow as the deep learning framework and OpenCV for image preprocessing. MongoDB is used for dataset management and storage. The trained model is deployed through a Flask web application, providing a browser-based interface in which users upload a fingerprint image and receive a real-time gender prediction with an associated confidence score within less than one second.

Additionally, real-time fingerprint samples were acquired using the SecuGen Hamster Pro H20 device, consisting of 100 male and 100 female samples. These samples were processed using the same preprocessing pipeline and used to evaluate system performance under practical conditions.

F. Evaluation Metrics

Model performance is assessed using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC curve, providing a comprehensive view of classification reliability across both gender classes.

IV. RESULTS AND DISCUSSION

The proposed FingerID system was trained and evaluated on a balanced subset of 22,134 fingerprint images from the SOCOFing dataset. The CNN model achieved a classification accuracy of 96.54%, with a processing time of under one second per inference query, confirming its suitability for real-time deployment.

The three-block CNN architecture demonstrated strong capacity to automatically learn discriminative ridge-flow patterns, micro-textures, and hierarchical spatial features directly from grayscale fingerprint images. The preprocessing pipeline— particularly CLAHE-based contrast enhancement and Gabor ridge filtering — contributed significantly to model robustness against variations in acquisition conditions such as pressure differences, partial smudging, and sensor quality variation.
Compared to traditional approaches, the proposed system achieves substantially higher accuracy. Ridge-based statistical methods reported accuracies of 80–91% [7], [9], frequency-domain techniques achieved 70–90% [2], [6], and hybrid ANFIS systems reached 80–88% [5]. The proposed CNN-based framework at 96.54% demonstrates a clear improvement over all prior non-deep-learning approaches, consistent with recent CNN-based studies reporting 92–96% accuracy [3], [6].

The balanced dataset (50% male, 50% female) ensured that the model did not develop class-wise prediction bias, which is a recognized limitation of several prior works that used imbalanced samples. The inclusion of synthetically altered fingerprint images in the SOCOFing dataset further improved the model's robustness against distorted or degraded inputs.

Real-time deployment through the Flask web application (FingerID) validated the practical feasibility of the system. The sub-second inference latency confirms that the model is computationally efficient and suitable for integration into forensic workstations, biometric kiosks, or mobile platforms.

V. CONCLUSION

This paper presents a complete CNN-based framework for fingerprint gender classification. The literature survey establishes that although ridge-based, frequency-domain, and hybrid fuzzy systems provide reasonable accuracy, their performance is limited by dependence on handcrafted features and sensitivity to imaging conditions. Deep learning specifically CNNs provides a more powerful alternative by automatically learning robust patterns from raw fingerprint images.

A detailed methodology was presented, including dataset preparation, preprocessing, CNN architecture design, training configuration, and evaluation metrics. The proposed architecture consists of three convolutional blocks followed by dense layers, providing a balance of accuracy and computational efficiency. Based on insights from recent studies, the model is achieved 96.54% accuracy.

Future work includes training the model on a large benchmark fingerprint dataset, optimizing hyperparameters, incorporating multi-finger fusion, exploring transfer learning techniques, and deploying the system in real-world biometric applications and forensic tools.

International Journal of Engineering Research & Technology (IJERT)
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Vol. 15 Issue 05 , May - 2026

Table I. Performance Comparison with Prior Methods

Method	Features Used	Classifier	Accuracy
Badawi et al. [7]	Ridge count, RTVTR	LDA, NN	80–88%
Verma & Sharma [9]	Ridge width, density	SVM	91%
Tom et al. [2]	DWT + PCA	Statistical	~70%
Sahu et al. [5]	RVA, frequency	ANFIS	80–88%
Narayanan et al. [3]	CNN features	CNN	~94%
Gustisyaf & Sinaga [6]	CNN features	CNN	>94%
Proposed Solution	CNN auto-features	CNN (3-block)	96.54%

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