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Integrative Deep-Ridge Architecture for Intelligent Fingerprint-based Gender Recognition

Sowjanya Vuddanti[1], Putta Pravallika[2], Gannavarapu Balasri Lakshmi Vishnupriya[3] and Chettupodila Dinesh[4]
[1-4]Dept. of Artificial Intelligence and Data Science, Lakireddy Bali Reddy College of Engineering, Mylavaram
Email: sowji635@gmail.com, pravallikaputta331@gmail.com, vishnupriyagannavarapu@gmail.com, dineshchettupodila1701@gmail.com

***Abstract*— Fingerprint-based gender identification has emerged as an important area of investigation in biometric studies owing to its relevance to various applications, including forensic analysis, biometric database management, and identity verification. This paper proposes a hybrid framework for fingerprint-based gender classification, which combines the effectiveness of handcrafted feature extraction methods with those of deep learning-based representations. Fingerprint images are classified into male and female classes, and several feature extraction methods are used to extract features from fingerprint images. Ridge-based statistical features are used, which are obtained from grayscale finger-print images. Ridge density, contrast, energy, and area features are used because they vary between male and female classes. Moreover, texture features are also used, which are obtained by applying Gabor filters at various orientations and frequencies. For improving the discriminative power of the features, a convolutional neural network (CNN) is used. Specifically, a pre-trained ResNet50 architecture is used as a feature extraction tool, and the fully connected layers are removed. Global average pooling is used to extract compact feature vectors. The extracted ridge features, texture descriptors, and deep learning features are normalized and fused at the feature level to create a comprehensive feature representation of fingerprint information. The feature vectors are classified using a Support Vector Ma-chine classifier with a radial basis function (RBF) kernel. The experimental evaluation of the proposed method shows that the method successfully utilizes the fingerprint information at the local structural level as well as the feature level, thus enhancing the gender classification performance.**

***Index Terms*— Gender classification using fingerprint; Soft biometrics; Ridge-based features; Gabor texture features; Deep learning; Convolutional Neural Network (CNN); ResNet50; Feature-level fusion; Support Vector Machine (SVM); Radial Basis Function (RBF) kernel; Forensic biometrics.**

I. INTRODUCTION

A. Background of Fingerprint-Based Gender Classification

Fingerprint-based gender classification has emerged as an important soft biometric problem due to its potential ap-plications in forensic investigations, biometric indexing, and large-scale identity management systems. Traditionally, gen-der determination from fingerprints was performed with the help of manual or statistical analysis methods on certain ridge characteristics like ridge density, count, and thickness.

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Empirical studies showed that female fingerprints generally have a higher ridge density with finer structures of ridges, while the male fingerprint possesses coarser ridges with wider spacing between them. Other approaches explored features such as minutiae distribution, RTVTR, and the prevalence of fingerprint pattern types including loops, whorls, and arches. While all these conventional methods are of great use, their performances are often seriously compromised by their sen-sitivity to image quality, noise, and variations in fingerprint acquisition conditions.

Fingerprint images have inherent fine details that range from structure to texture, which are not used merely for identification but also have the potential to be used for the deduction of soft biographic features, including gender. In the past few years, the application of gender classification from fingerprint features has attracted considerable interest in the areas of biometrics and forensics, as it has the potential to significantly narrow down the range of candidates in a large database, thus helping in the preliminary screening of investigations.

Recent developments in the field of biometric technology have underscored the significance of fingerprint-based analysis for purposes such as identity recognition, forensic investigation, and demographic inference. Among these, the use of fingerprint-based gender prediction has been proposed as a complementary biometric technology that can be used to assist human identification systems by improving the efficiency of the decision process.

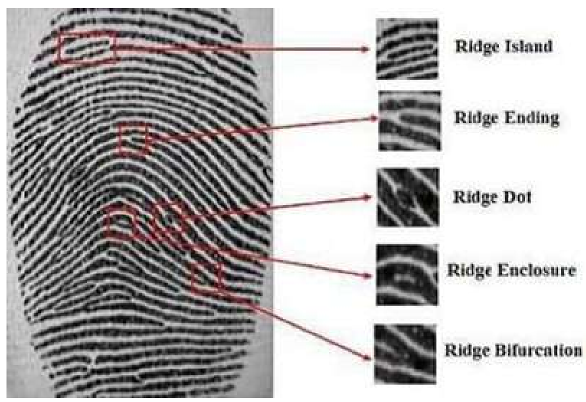

Fig. 1. Identification of Minutiae Points in a Fingerprint Image.

The key minutiae features identified in a fingerprint image (Fig. 1) are described as follows:

- Ridge Ending: Ridge ending is a type of feature present in a fingerprint where the ridges stop abruptly.
- Ridge Island: Ridge island is a short segment of a ridge present between two other ridges.
- Ridge Dot: Ridge dot is a short segment of a ridge present in a fingerprint and appears as a dot structure.
- Ridge Enclosure: Ridge enclosure is a type of feature present in a fingerprint where a ridge splits and then unites again.
- Ridge Bifurcation: Ridge bifurcation is a type of feature where one ridge splits into two ridges, resulting in a Y-shape structure.

B. Research Problem and Motivation

The design of a gender classification system is not an easy task. Although traditional approaches are of immense use, their performance is often severely affected by susceptibility to im-age quality, noise, and fingerprint acquisition conditions. This indicates the difficulty involved in identifying the gender of a person from fingerprint images using conventional approaches, especially when there are variations in acquisition conditions and image quality.

C. Significance of the Gender Classification

To overcome the aforementioned shortcomings, this re-search proposes a hybrid approach for fingerprint-based gender classification by incorporating statistical features derived from fingerprints and ridges, as well as Gabor texture information and deep CNN-based representations in a single framework. The statistical components comprising ridge density, ridge contrast, ridge energy, and ridge area are extracted from grayscale fingerprints to capture their local characteristics. At the same time, the use of Gabor filters with varied orientations helps in extracting the directional and frequency spectral properties of fingerprint ridges, which are very discriminative in nature for biometric computations.

In the proposed work, a hybrid framework for fingerprint-based analysis has been developed by using a combination of traditional feature extraction methods and deep learning-based features. A pre-trained deep CNN architecture has been used as a feature representation model by removing the classification layer and using a global average pooling layer to obtain compact and discriminative features. The handcrafted features extracted from the ridge structures and texture changes are normalized and combined with the deep features at the feature level to obtain a hybrid feature set, which is subsequently classified using a Support Vector Machine with a radial basis function kernel.

II. LITERATURE REVIEW

A. Traditional Fingerprint-Based Gender Classification Methods

Conventional fingerprint-based gender classification methods rely primarily on handcrafted features extracted from fingerprint ridge structures and texture patterns. These methods typically utilize ridge density, ridge width, ridge count, and other ridge-related characteristics to differentiate between male and female fingerprints. Ridge density has been consistently reported as one of the most reliable gender indicators in foren-sic analysis. Experimental findings indicate that ridge densities of ≤12 ridges per 25 mm2 are predominantly associated with male fingerprints, whereas higher ridge densities are more commonly observed in female fingerprints [4], [8], [10].

Additional ridge-based features such as ridge width and ridge number further enhance the reliability of gender dis-crimination [5]. Traditional machine learning classifiers have shown promising results when combined with effective hand-crafted feature representations. Ensemble-based classifiers, particularly Random Forests, have achieved classification ac-curacy levels of up to 98% in fingerprint gender classification tasks, demonstrating that combining multiple decision models improves robustness compared to individual classifiers [2].

In addition to ridge-based features, frequency- and texture-domain techniques such as Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and Local Binary Patterns (LBP) have also been successfully applied to fingerprint gender classification. LBP-based systems have reported accuracy levels exceeding 96% on balanced finger-print datasets [11], [12]. Despite their effectiveness, traditional approaches are highly dependent on image quality, noise levels, and fingerprint acquisition conditions.

B. Deep Learning Approaches for Fingerprint Gender Classification

Recent research emphasizes that deep learning methods play a critical role in modern biometric systems by enabling automatic extraction of discriminative features directly from

Data Collection Methods

Input: Fingerprint image dataset

$$D = \{(I_i, y_i)\}_{i=1}^{N}$$

Step 1: Capture fingerprint images from a diverse set of individuals and organize them into Male and Female classes. Ensure consistent acquisition conditions to reduce noise, dis-tortion, and quality variations across fingerprint images. Pre-processing operations applied include grayscale conversion, noise removal, normalization, and image resizing.

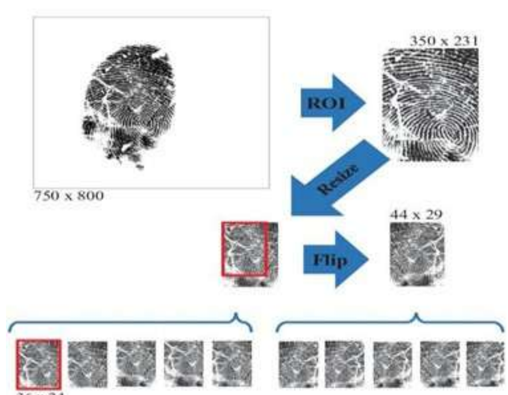

Fig. 2. Pre-processing Pipeline for Fingerprint Image Enhancement.

C. Sample Selection

Step 2: Assign the correct gender label (Male or Female) to each fingerprint image and construct a labelled dataset. Maintain class balance during dataset preparation to avoid bias during classification. In the proposed system, the fingerprint images are classified into two distinct classes, namely male and female.

D. Data Analysis Techniques

- Ridge-Based Feature Extraction: Ridge-based feature extraction aims at extracting the basic structural features that exist in fingerprint images. Fingerprint images are first converted to grayscale and resized to a certain resolution to ensure uniformity. Quantitative descriptors are extracted from ridge structures to represent fingerprint patterns. These include ridge density, ridge contrast, ridge energy, and ridge area.

Ridge-based features are significant in gender classification, as previous studies have revealed differences in ridge density and ridge thickness between male and female fingerprint images. The mathematical formulations are as follows:

Ridge Density

$$RD = \frac{N_r}{N} \tag{1}$$

where N_r = number of ridge pixels and N = total number of pixels.

Ridge Contrast

$$RC = \sqrt{\frac{1}{N}\sum_{p=1}^{N}(I_p - \mu)^2} \tag{2}$$

where I_p = pixel intensity and μ = mean intensity.
Ridge Energy (using Sobel gradients

$$G_x = \frac{\partial I}{\partial x},\ G_y = \frac{\partial I}{\partial y}):$$

$$RE = \frac{1}{N}\sum_{p=1}^{N}\sqrt{G_x(p)^2 + G_y(p)^2} \tag{3}$$

The ridge feature vector is:

$$F_{\text{ridge}} = [RD, RC, RE, RA] \tag{4}$$

- Gabor Texture Feature Extraction: Gabor texture feature extraction is used to model the directional and frequency-related characteristics associated with ridge patterns present in fingerprints. The images are processed by applying a set of filters consisting of various orientations to extract texture information associated with the directional flow of ridges. For each orientation θ_k, a Gabor kernel is defined as:

$$G(x, y; \theta_k) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}\right) \tag{5}$$

where the rotated coordinates are:

$$x' = x\cos\theta_k + y\sin\theta_k \tag{6}$$

$$y' = -x\sin\theta_k + y\cos\theta_k \tag{7}$$

Gabor feature statistics are computed as:

$$\mu_k = \text{mean}(G_k), \qquad \sigma_k^2 = \text{var}(G_k) \tag{8}$$

The Gabor feature vector is:

$$F_{\text{gabor}} = [\mu_1, \sigma_1^2, \ldots, \mu_K, \sigma_K^2] \tag{9}$$

- Deep Feature Extraction Using ResNet50: A deep fea-ture extraction process utilizes a convolutional neural network following the ResNet50 paradigm to extract high-level features from fingerprint images. The network, pre-trained on the ImageNet dataset, is used solely for feature representation by removing its classification layers. All convolutional layers remain fixed. Global average pooling is applied to summarize the feature maps from the final convolutional layer:

$$F_{\text{cnn}} = \text{GAP}(\text{ResNet50}(I_i)) \quad (10)$$

where GAP denotes Global Average Pooling.

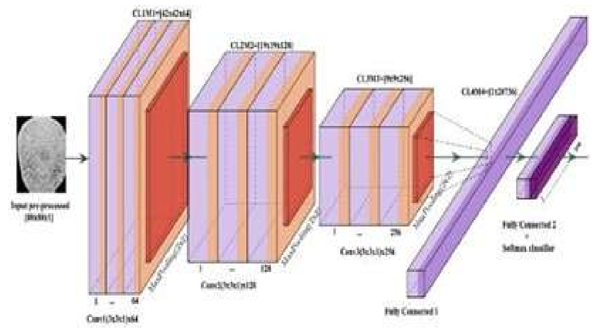

Fig. 3. Deep Feature Extraction Architecture Using Convolutional Neural Network.

- Feature Normalization: Feature normalization is applied on both the manual ridge feature set and Gabor feature set using standard score normalization. All features are normalized to have zero mean and unit standard deviation:

$$F' = \frac{F - \mu}{\sigma} \quad (11)$$

- Feature-Level Fusion: Normalized ridge features, nor-malized Gabor features, and deep CNN features are combined into a single hybrid feature vector. This strategy integrates complementary information from various feature extraction techniques, leading to a richer and more distinctive represen-tation:

$$F_{\text{hybrid}} = F_{\text{cnn}} \oplus F'_{\text{ridge}} \oplus F'_{\text{gabor}} \quad (12)$$

where ⊕ denotes concatenation.

- Support Vector Machine Classification: The fused feature vectors are used to train the SVM classifier to classify the fingerprint images as male or female. An SVM classifier with a radial basis function (RBF) kernel is used due to its ability to handle non-linear relationships:

$$K(x_i, x_j) = \exp(-\gamma |x_i - x_j|^2) \quad (13)$$

The optimization objective is:

$$\min_{w,b,\xi} \frac{1}{2}|w|^2 + C\sum_{i=1}^{N} \xi_i \quad (14)$$

subject to the SVM constraint:

$$y_i(w \cdot \phi(x_i) + b) \geq 1 - \xi_i \quad (15)$$

IV. Proposed Architecture

The proposed hybrid fingerprint-based gender classification approach effectively utilizes the complementary information available in fingerprints via ridge-based statistical features, Gabor-based texture features, and deep features extracted using a CNN-based deep architecture. Together these enable effective use of both local and global fingerprint information. After acquiring the two types of handcrafted features, a merged feature vector is formed from both sets. These hand-crafted features are then normalized to have a mean of zero and a variance of one using standard scaling, preventing any one feature set from biasing the training process. Simultaneously, deep features are extracted from a pre-trained ResNet50 model utilizing a global average pooling layer. The normalized hand-crafted features and deep features are subsequently combined via hybrid feature fusion, resulting in a combined rich and discriminative feature representation. The final hybrid feature vector is then utilized as the input to a Support Vector Machine classifier.

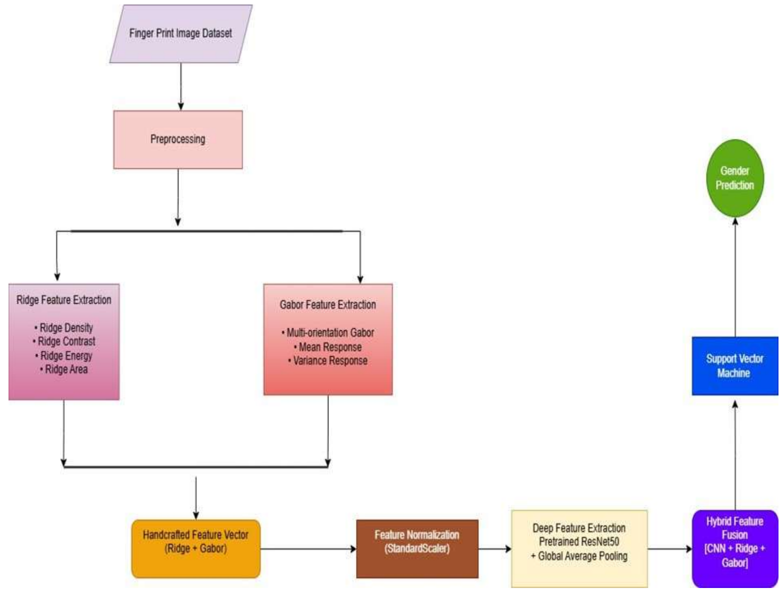

Fig. 4. Proposed Architecture

V. RESULTS

A. Evaluation Metrics

The effectiveness of the proposed fingerprint-based gender classification model is evaluated by employing the hybrid feature representation that combines ridge-level statistical fea-tures, Gabor texture features, and deep features learned via a pre-trained ResNet50 model. The computed features are normalized and combined to obtain a single feature represen-tation, classified via an SVM with an RBF kernel. Quantitative evaluations are carried out using widely used performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis.

B. Comparative Results with Existing Methods

Table I presents a comparison of the proposed approach with existing methods from the literature.

C. Data Analysis and Interpretation

The results obtained through the experiment reveal that the proposed method achieves high classification performance, verifying the effectiveness of combining handcrafted and deep features under a single classification framework. Analysis of the confusion matrix results reveals balanced prediction performance for the two classes, which verifies the robustness of the classifier and the effectiveness of the class-weighted SVM training strategy.

Fig. 5. Sample Male and Female Fingerprints.

The hybrid combination of ridge-level statistical features, Gabor texture features, and deep CNN-based features demon-strates improved classification performance compared to ap-proaches based on a single feature category.

VI. CONCLUSION

A. Summary of Key Findings

The classification stage employs a Support Vector Machine with a radial basis function kernel, which enables effective separation of fingerprint samples in a high-dimensional feature space. Experimental evaluation demonstrates that the pro-posed approach achieves improved performance across mul-tiple evaluation metrics, including accuracy, precision, recall, and F1-score, when compared to methods relying solely on handcrafted or deep features. Confusion matrix analysis fur-ther confirms the balanced classification performance between male and female classes.

B. Contributions to Biometric and Forensic Applications

The efficient design and scalability of the proposed frame-work make it suitable for real-world biometric and forensic applications, where rapid and reliable gender identification is essential. The proposed approach is able to effectively identify the gender of an individual using a fingerprint, and its effi-ciency makes it applicable to large-scale identity verification scenarios. Overall, the results validate the effectiveness of the hybrid feature representation and classification strategy for fingerprint-based gender prediction.

C. Recommendations for Future Research

Although the proposed system has proven to achieve good performance, there are still opportunities for further improve-ment. Future work can include the incorporation of additional fingerprint features, such as the orientation of minutiae points and ridge flow. The dataset can also be extended to include more fingerprint images from different age groups, ethnicities, and sensors. Another possible area of development is combin-ing fingerprint information with other biometric features. The robustness of the proposed system can be further improved by incorporating more advanced deep learning techniques, such as vision transformer models and more recent convolutional networks. Future work can also include the development of real-time systems incorporating explainable artificial intelli-gence.

TABLE I: COMPARATIVE RESULTS WITH EXISTING METHODS

Ref.	Dataset Used	Feature Extraction	Classifier	Key Results	Observations
[14]	Proprietary dataset	Ridge density, RTVTR, white line count	Statistical classifier	88.5% accuracy	Ridge density strong gender indicator
[12]	400 fingerprint samples	Local Binary Pattern (LBP)	k-NN classifier	95.88% accuracy	Texture-based LBP effective for forensics
[11]	Custom dataset	2D-DWT + PCA	Minimum distance classifier	Improved discrimination	Fusion of spatial and frequency features
[5]	Indian population dataset	Ridge density, breadth, count	Statistical analysis	High gender separability	Females show higher ridge density
[4]	Indian fingerprints	Ridge density	Threshold-based classification	Reliable separation	Ridge density validated as robust trait
[6]	Multiple datasets	CNN-based deep features	CNN	70–95% accuracy	Fingerprint periphery crucial
[20]	Small & imbalanced datasets	FFT + PCA	SVM + SMOTE	Improved accuracy	Feature fusion and balancing critical
Propose	Fingerprint image dataset	Ridge statistics + Gabor texture + ResNet50 deep features	SVM (RBF kernel)	Improved overall accuracy	Combines local and global features via hybrid fusion

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