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A Multiscale Residual Framework for Fingerprint Gender Classification Based on Morphology Wavelet Features and Siamese Metric Learning

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Abstract

This paper proposes a multiscale residual framework for gender classification on fingerprint images. It addresses the tough problem where most gender-related features in fingerprint ridges are subtle, and previous methods relied mainly on spatial features and failed to utilize the multi-scale features, attention, and dimension reduction. Therefore, morphological preprocessing, discrete wavelet-based multiscale feature extraction, Siamese network-based dimensionality reduction, and residual neural network classification, involving attention and non-local block, is proposed to effectively solve this problem. This framework performs morphological preprocessing on fingerprint images and decomposes the image into low-, mid-, and high-frequency channels by discrete wavelet transform; then, these channels are embedded into feature vectors by a Siamese ResNeXt-SE structure, and their cross-attention is fused to retain inter-/intra-class discriminability. Then, it applies a residual neural network with attention and a non-local block on the features for classification. On the SOCOFing dataset, which has 6,000 fingerprint images, the accuracy, precision, recall, and F1-score are 99.50%, 99.68%, 98.82%, and 0.99, respectively, and AUC is 0.99 for both genders, which achieves excellent results. Ablation studies have proven that morphological operators, wavelet decomposition, and Siamese compression do contribute to the framework individually. Experiments against two common types of noises, Gaussian and salt-and-pepper, also demonstrate the robustness against noise with trivial loss of accuracy, and comparing with prior CNN and CNN-SVM models, the method shows superiority by utilizing multiscale and frequency domain information comprehensively. However, it is constrained to use high-quality grayscale images and is not tested on adversarial robustness. The framework shows high potential for applications such as automatic fingerprint identification systems, forensics, and large biometric databases since the gender classification is effective, scalable, and discriminative.

Keywords: Fingerprint Gender Classification, Multiscale Feature Extraction, Siamese Network, Morphological Preprocessing, Residual Neural Network, Discrete Wavelet Transform, Biometric Analysis.

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1 Introduction

Gender-specific features in fingerprint images can assist in reducing the suspect list and improving automated fingerprint identification systems (AFIS), so gender recognition is gaining more interest in the fields of biometrics and forensic science (Arooj et al., 2025). Studies showed that differences in ridges between male and female are found in ridge density, ridge count, and the spatial distribution of minutiae. Statistical methods for sex estimation are established, taking into account that women generally possess higher ridge density than men (Narayanan & Sajith, 2019). By simply calculating pixel densities with a systematic counting method in the time domain, the accuracy of recognition can reach 90.2% for females and 96.4% for males (Gnanasivam & Vijayarajan, 2019), which indicates that even with low-complexity computational methods, a significant amount of gender-related information is embedded within the fingerprint pattern.

In order to further improve the accuracy, sophisticated methods have been developed. OSA(Optimal Score Assignment) methods incorporate various fingerprint features into a system for improved gender estimation (Berriche, 2022). CNN-based models, as well as combined CNN with other classification models, such as SVM, ANN, etc., reached high accuracy scores around 94%–99% (Rim et al., 2020; Gustisyaf & Sinaga, 2021). Nevertheless, conventional methods mostly utilize spatial feature without explicit support for multi-scale information, attention mechanisms, and dimensionality reduction, which might fail to distinguish the latent subtle sex-specific characteristics in the ridge patterns (Iloanusi & Ejiogu, 2020).

Recently developed multi-stage frameworks combine signal processing with deep learning for extract rich fingerprint information. They used morphological processing as pre-enhancement and multi-scale analysis by performing Discrete Wavelet Transform. After applying Siamese networks for dimensionality reduction of the extracted multi-scale fingerprint features, global, mid-level, and fine-grained ridge patterns are obtained (Narayanan & Hameeduddin, 2023; Olufunso et al., 2022). A cascade of a residual neural network classifier with an attention mechanism and a non-local block added for feature aggregation allows for modeling long-range dependencies in ridge flow and texture, and it shows significant improvement over traditional CNNs or CNN-SVMs by generating compact embeddings that preserve discriminative power and handle various qualities of input fingerprints (Serin et al., 2024; Ibitayo et al., 2022).

All the aforementioned multi-stage frameworks have been proven to be effective in gender classification of fingerprints with high AUC values, nearly perfect confusion matrices, and balanced precision and recall rates (Thonglim et al., 2024; Oleiwi et al., 2022). Accuracy over 99% by incorporating morphological processing, multi-scale wavelet analysis, and Siamese-based dimension reduction coupled with residual-FPN classifiers shows potential for deployment in real-world biometrics and forensics (Suwarno, 2023).

Incremental improvements in the proposed fingerprint gender-classification framework are presented with clear and sufficient justification, highlighting the contributions of morphological preprocessing, multiscale feature extraction, Siamese-based dimensionality reduction, and residual classification. The practical relevance and deployment feasibility are convincingly demonstrated through evaluation on the SOCOFing dataset and robustness under varying noise and image quality conditions.

Background

In recent research toward fingerprint and palm-based gender classification, more deep learning algorithms have been introduced to increase classification accuracy and generalization ability. Convolutional Neural Network (CNN), widely used to automate feature extraction, can simultaneously recognize gender, finger, and biometric characteristic features with significant accuracy (Hsiao et al., 2022). Moreover, using the autoencoder-based network to learn latent fingerprint features was proposed to remove discriminative information during the feature learning process for dimensionality reduction, while retaining them for gender classification (Qi et al., 2022). It revealed the superiority of integrating feature learning with nonlinear embedded techniques, which makes the recognition rate even higher with partial and low-quality fingerprints.

More recent efforts continue to improve traditional fingerprint-based analysis. An approach combined spatio-frequency feature fusion of fingerprint for an IoT-supported gender classification system to achievereal-timescalable gender recognition with resistance to noise and environmental conditions was presented (Kong et al., 2024). More surprisingly, combining hand palm imaging with PySpark-supported parallelized processing with VGG19 to perform high-throughput learning for gender classification at scale can get excellent performance (Henedak et al., 2024). Above all, it showed the potential of multi-modal data representation, deep feature learning, and scalable computing systems for gender classification in biometric systems.

Although CNN, autoencoder-based network, and IoT-integrated network are promising in their classification performance, problems of low-quality images, real-time performance, and multi-modal combination issues remain the limitations to achieve much better gender classification systems, and there is room to optimize them or adopt combined deep learning models.

Key Contribution

1. Proposed a multiscale residual fingerprint gender-classification scheme that combines the morphological preprocessing, discrete wavelet feature extraction, Siamese network-based dimensionality reduction, and residual neural network-based classifier to produce discriminating compact embeddings.
2. Showed the state-of-the-art statistical results on the SOCOFing database: 99.50% accuracy, 99.68% precision, 98.82% recall, and AUC 0.99, and the resistance to Gaussian and salt-and-pepper noise.
3. Justified the impact of each model component with the help of an ablation study and comparisons, and a deployable, scalable, and robust automated fingerprint gender classification system was built.

The organization of this paper is as follows: In Section I, the significance and challenge of fingerprint gender classification and the background are presented. In Section II, the proposed multiscale residual framework-including morphological preprocessing, multiscale feature extraction, Siamese embedding, and residual classification-is discussed. In Section III, qualitative and quantitative assessments, ablation studies, and comparisons are presented. Section IV provides a summary and future work.

2 Methodology

The proposed fingerprint-based gender-classification framework will be presented as a single-end pipeline based on Morphological methods, Multiscale signal decomposition, Metric learning, and deep residual classification. This single-end-pipeline design has been developed to handle the different difficulties of fingerprint gender-classification problems (difficult distinction due to imprinting noise, the small difference between genders regarding sophisticated nuances, the high dimensional features, which require various powerful model types). First, from every fingerprint image, the framework performs morphological-preprocessing based on ridges and valleys in order to highlight these ridges/valleys and then to extract the geometrical feature-maps. These decompositions are then enhanced across a variety of waves using the Discrete Wavelet Transform to extract the roots of the imprinted texture. To address the problem of the Multiscale analysis, specifically the information explosion problem, a Siamese Network with Contrastive Metric Learning is used to accurately displace the hyper-dimensional feature tensor into a compact and efficient embedding space. The result is that the learned embeddings are then shaped to fit the dimensions required of a classifier using Residual Neural Networks, where Deep Residual Learning, Attention, and Multiscale Feature Fusion are used to achieve high accuracy in the Gender classification tasks. The motivation of the remaining subsections is to describe the proposed methodology in detail.

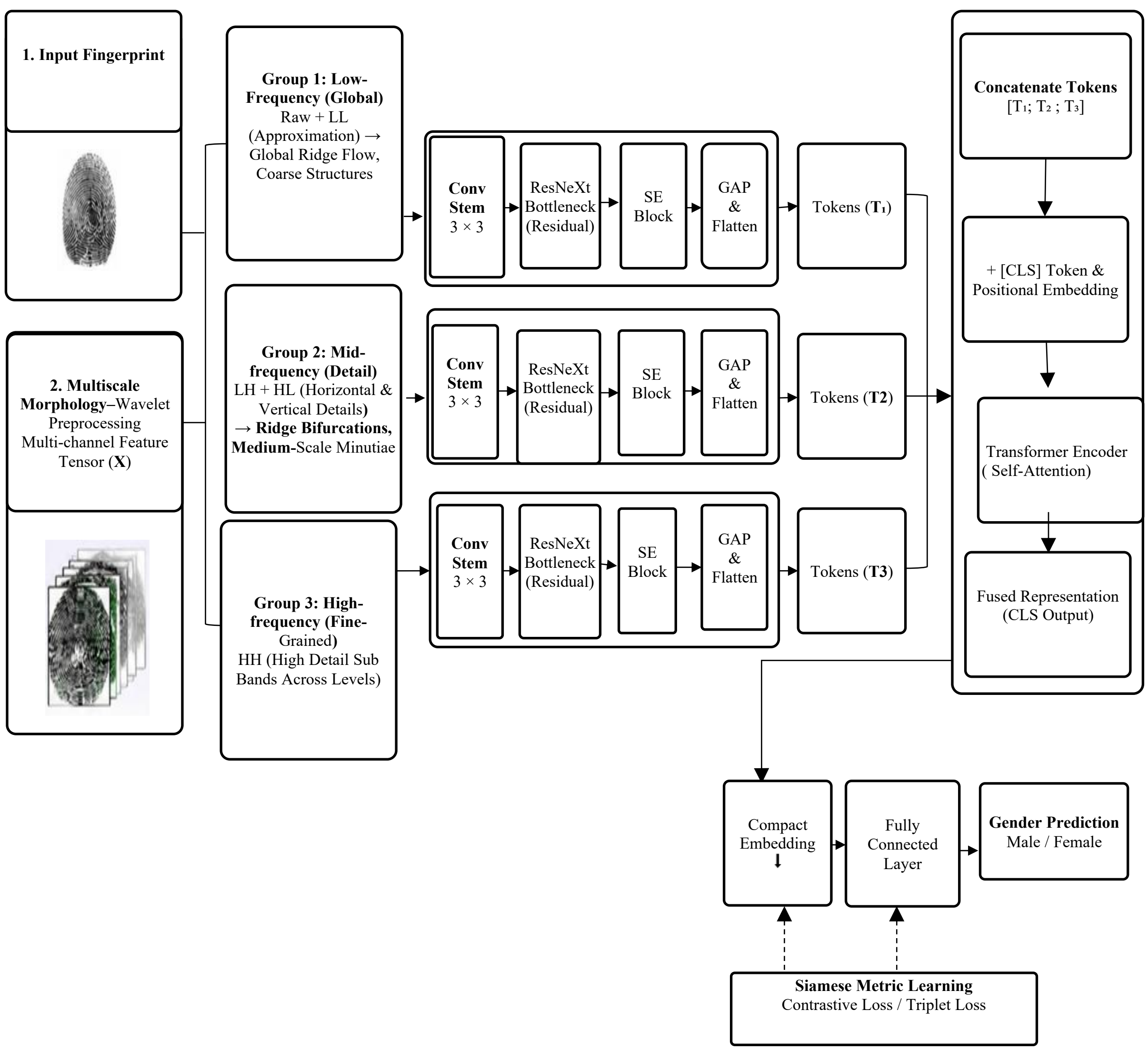

Figure 1: Multiscale residual framework for fingerprint gender classification

The framework for fingerprint gender classification suggested in figure 1 illustrates the entire procedure starting from the input fingerprint, through morphology-wavelet preprocessing and feature clustering to three frequency groups (low, mid, high), through a Siamese encoder with ResNeXt and an SE block, and finally into tokenization, cross-attention fusion, and gender prediction.

2.1 Fingerprint Preprocessing and Morphological Feature Enhancement

Images of fingerprints are very complex and contain different ridge and valley structures which may have unique patterns that differ across genders because of contrasting ridge density and thickness, as well as different local texture traits. Nonetheless, noise, uneven lighting, and background distractions commonly obscure raw fingerprint images and can hide gender-related features. To mitigate the weaknesses of the raw fingerprint images, a mathematical morphology-based preprocessing approach works with the lights and shadows of the images in order to enhance the structures that are relevant, and lessen the variations that are not

Given an input fingerprint image $I \in \mathrm{R}^{H \times W}$ The image is first converted to grayscale and represented in floating-point format to facilitate numerical processing. A structuring element B, defined as a 3×3 elliptical kernel, is then used to perform a series of morphological operations designed to extract complementary structural characteristics of the fingerprint. Multiple morphological feature maps are derived from the input image, each capturing distinct geometric properties of fingerprint patterns:

2.2 Siamese Network–Based Dimensionality Reduction

During pre-processing, morphological and wavelet-based features are extracted to obtain a high-dimensional, multi-channel fingerprint representation. In order to obtain redundancy-less and efficient representation, the obtained features are projected onto a low-dimensional, discriminative embedding space using a Siamese metric learning network.

The multi-channel features are separated based on the frequency domain into three types:

- **Low-frequency / global features**: this is robust to noise and identifies dominant orientation, coarse texture, ridge flow over large regions.
- **Mid-frequency / detail features**: capture ridge bifurcations, mid-scale minutiae, and orientation transitions while achieving a balance between robustness and discriminative power.
- **High-frequency/fine-grained features**: sensitive to minutiae-level information like ridge ends and curvature transitions and provide complementary micro-texture cues.

Each group is fed to a shared-weight Siamese encoder composed of a convolutional stem, ResNeXt bottlenecks, and an SE module for gender sensitive feature emphasis. The encoders are flattened into sequences and concatenated to be fed to a Transformer-based cross-attention fusion module. The model uses positional embeddings and a classification token to provide scale-specific learning and dependencies between frequency channels, yielding a compact discriminative embedding space.

Pseudocode for Multiscale Residual Fingerprint Gender Classification Framework

Input: Fingerprint image I

Output: Predicted gender label (Male/Female)

1. Preprocessing:
   a. Convert I to grayscale
   b. Apply morphological operations:
      - Gradient
      - Top-hat
      - Black-hat
      - Skeletonization
      - Ridge enhancement
   c. Generate multiple morphological feature maps F_morph
2. Multiscale Feature Extraction:
   a. For each F in F_morph:
      i. Apply Discrete Wavelet Transform (DWT) to extract multiscale subbands
   b. Group subbands into frequency-based channels:
      - Low-frequency (global)
      - Mid-frequency (detail)
      - High-frequency (fine-grained)
   c. Generate multiscale feature tensor F_multi
3. Dimensionality Reduction via Siamese Network:
   a. Feed each frequency group into a shared-weight Siamese encoder:
      - Convolutional stem
      - ResNeXt bottlenecks
      - Squeeze-and-Excitation (SE) module
   b. Flatten and concatenate embeddings from all groups
   c. Apply contrastive loss to enforce compact and discriminative embedding
   d. Obtain compact embedding E
4. Classification using Residual-FPN Network:
   a. Reshape embedding E into spatial feature maps
   b. Pass through Residual Neural Network with:
      - Deep residual blocks
      - Channel attention
      - Non-local modeling
      - Feature pyramid aggregation
   c. Output final gender prediction

5. Evaluation:

a. Compute Accuracy, Precision, Recall, F1-score

b. Optional: ROC curve and confusion matrix for analysis

End

This pseudocode outlines the proposed fingerprint gender classification pipeline involving morphological preprocessing for ridge pattern improvement, multiscale feature extraction using DWT, dimensional reduction using a Siamese network with ResNeXt and SE blocks, and the final classification stage with a Residual Neural Network, evaluated using accuracy, precision, recall, and F1-score.

Mathematical Description

1. **Fingerprint Preprocessing with Morphology**: Let the input fingerprint image be I. Morphological operations (gradient, top-hat, black-hat, skeletonization, ridge enhancement) generate feature maps (Equation 1):

$$F_{\text{morph}} = \{f_1, f_2, \dots, f_n\} = \text{MorphOps}(I) \quad (1)$$

2. **Multiscale Feature Extraction (Wavelet Transform)**: Each morphological feature map is decomposed using Discrete Wavelet Transform (DWT) into multiscale subbands (Equation 2):

$$F_{\text{multi}} = \{F_{\text{low}}, F_{\text{mid}}, F_{\text{high}}\} = \text{DWT}(F_{\text{morph}}) \quad (2)$$

3. **Siamese Network Embedding (Dimensionality Reduction)**: Each frequency group is encoded by a shared-weight Siamese network with ResNeXt and SE modules, producing a compact embedding E (Equation 3):

$$E = \text{SiameseEncoder}(F_{\text{low}}, F_{\text{mid}}, F_{\text{high}}) \quad (3)$$

Contrastive loss is applied to enforce intra-class compactness and inter-class separation (Equation 4):

$$\mathcal{L}_{\text{contrastive}} = y \cdot \| E_i - E_j \|^2 + (1-y) \cdot \max(0, m - \| E_i - E_j \|)^2 \quad (4)$$

where $y = 1$if same gender, else 0; $m$is margin.

4. **Residual-FPN Classification**: Embedding $E$is reshaped into feature maps and passed through a Residual Neural Network with attention and feature pyramid aggregation (Equation 5):

$$\hat{y} = \text{ResFPNClassifier}(E) \quad (5)$$

where $\hat{y}$is the predicted gender label.

The suggested framework for fingerprint gender classification also acknowledges the likely security threats from attackers that try to manipulate the input, steal features or even avoid the classifier itself. Consider the threat by using controlled fingerprint capture, limitation of access to the Siamese embedding space, and in-built classifier robustness owing to morphology enhancement, multi-scale feature extraction, and attention-based residual learning. More advanced analysis of formal adversarial robustness will be performed using the system with spoof or perturbed fingerprints as a subsequent step.

2.3 Dataset Description

The Sokoto Coventry Fingerprint Dataset (SOCOFing) is one of the most popular public databases for fingerprint study and applications in classification by gender, pattern recognition, alteration detection, etc. It contains 6,000 images of 600 people, all from Africa, taken of all ten fingers of each person. The images are 96103 pixels and in grayscale while maintaining ridge-valley structures. The database comes labeled with the gender of the person and also includes artificially modified fingerprints of several difficulty levels to mimic various types of real-world damage. However, to ensure extraction of gender-specific features on original images, only original images from SOCOFing were taken for the purposes of this experiment. The fact that SOCOFing is clear, has good image quality and has been very popular for such applications makes it appropriate for robust fingerprint gender classification, where the FPN-integrated multi-scale ResNeXt-SE network is applied (www.kaggle.com).

2.4 Evaluation Metrics

The performance of the proposed fingerprint gender classifier is evaluated using **accuracy, precision, recall, and F1-score**.

Accuracy measures the proportion of correctly classified fingerprints (Equation 6):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

where $TP$and $TN$are true positives and true negatives, and $FP$and $FN$are false positives and false negatives.

Precision indicates the correctness of predicted label (Equation 7):

$$\text{Precision} = \frac{TP}{TP+FP} \quad (7)$$

Recall (or sensitivity) evaluates how well the model identifies all true instances (Equation 8):

$$\text{Recall} = \frac{TP}{TP+FN} \quad (8)$$

F1-score combines precision and recall into a balanced measure (Equation 9):

$$\text{F1-score} = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}} \quad (9)$$

3 Results and Discussion

This section provides an overview of and a thorough explanation of the proposed fingerprint gender detection framework focusing on qualitative assessment, quantitative results, and ablation studies for further analysis of the results obtained. The impact of each multiscale feature extraction phase, Siamese embedding feature learning and residual-based classification was analyzed and the effectiveness of proposed pipeline was evaluated. The experiments were conducted on a workstation with an NVIDIA RTX 4060 with 8 GB of VRAM, 32 GB of RAM, and an Intel Core i7-13650HX CPU. Implementation utilized Python 3.10 and PyTorch 2.5.1 and model training and inference were accelerated with CUDA 12.1. The results were analyzed to obtain the performance indicators recorded for the experiments.

In the present design, the convolutional kernels are initialized to 3×3, depths of ResNeXt bottleneck blocks are set to 32 and 64 channels, and reduction ratio of SE module is fixed to 16. The Siamese network embedding dimension and the margin of the contrastive loss are fixed to 256 and 1.0 respectively. The thresholds of the decision are fixed to 0.5, and frequency channels are divided into low (global), mid (detail), and high (fine-grained) bands. This can guarantee learning of the optimal features, robust classification, and consistent prediction of gender.

3.1 Qualitative Analysis and Feature Visualization

To facilitate a qualitative assessment of the proposed framework for extraction and representation learning, this subsection provides an overview of visual interpretations of the framework's intermediate and learned representations. More specifically, focus on the multiscale feature maps produced from the integration of mathematical morphology and discrete wavelet decomposition, and on the discriminatively structured, low-dimensional embeddings produced by the Siamese network. This set of visual representations is meant to qualitatively illustrate the varying details of fingerprint attributes associated with gender in terms of their being enhanced, encoded, and subsequently separated. While this set of visual representations is not used to make predictions in a classification task, it helps to illustrate the richness of the features extracted within the embedding space and the resulting class separability to validate the proposed methodology's design choices.

The figure 2 shows 48 feature maps taken from a fingerprint image, showing both morphological and wavelet transforms of the fingerprint. The original fingerprint is shown in the top left, and the original image is followed by gradient, top-hat, black-hat, skeletonized, ridge-enhanced, and morphological variants. The preprocessing steps represent various fingerprint structures such as ridge, valley, and minutiae. The other feature maps represent wavelet decompositions of the image at several scales, which capture texture at diverse spatial frequencies. The subbands contain the low-frequency approximation coefficients that contain the broad ridge pattern and high-frequency detail coefficients that include minutiae, ridge bifurcation, and local irregularities.

The benefits of merging morphological enhancements with wavelet transform include maintaining significant structural elements, as well as smaller textural details important for differentiating gender in fingerprint identification. Utilizing these multi-scale representations, the model is able to retrieve a range of gender-related fingerprint characteristics and offer this information for the later steps of classification and dimensionality reduction. Moreover, this visual variety is the reason for the need of classification after the reduction.

The figure 3 shows a 3D scatter plot of the learned Siamese embeddings for the first 3 principal components using PCA. It should be noted that PCA is not part of the methodology and is only used as a visualization tool to help evaluate the learned feature space's structure on a qualitative basis for discrimination. This projection helps to gain an intuitive understanding of the learned fingerprint representations with respect to each gender as the feature embeddings are dimensionally reduced using the metric learning framework.

From the provided figure, the classes of males (represented by blue points) and females (represented by green points) appear to have a significant amount of separation along the first principal component (PC1). This principal component captures the bulk of the variance due to the structural differences associated with the gender, as opposed to some nuisance texture variations. The male samples have most of their points positioned above the axis of PC1, and the female samples have most of their points positioned below the axis of PC1. This suggests that the Siamese network is able to learn embeddings that contain strong information with respect to gender. Although some points in the two classes overlap, indicating the challenges and nuances of gender and fingerprint traits, their overall clustering indicates that the embedding space is structured, and thus, the intra-class variance is low, and the inter-class variance is high. This verifies, to a certain extent, that the embeddings produced by the proposed reduced dimensionality framework, based on Siamese architecture, preserve embedding information that is classifiable with gender and that is significantly useful for classification.

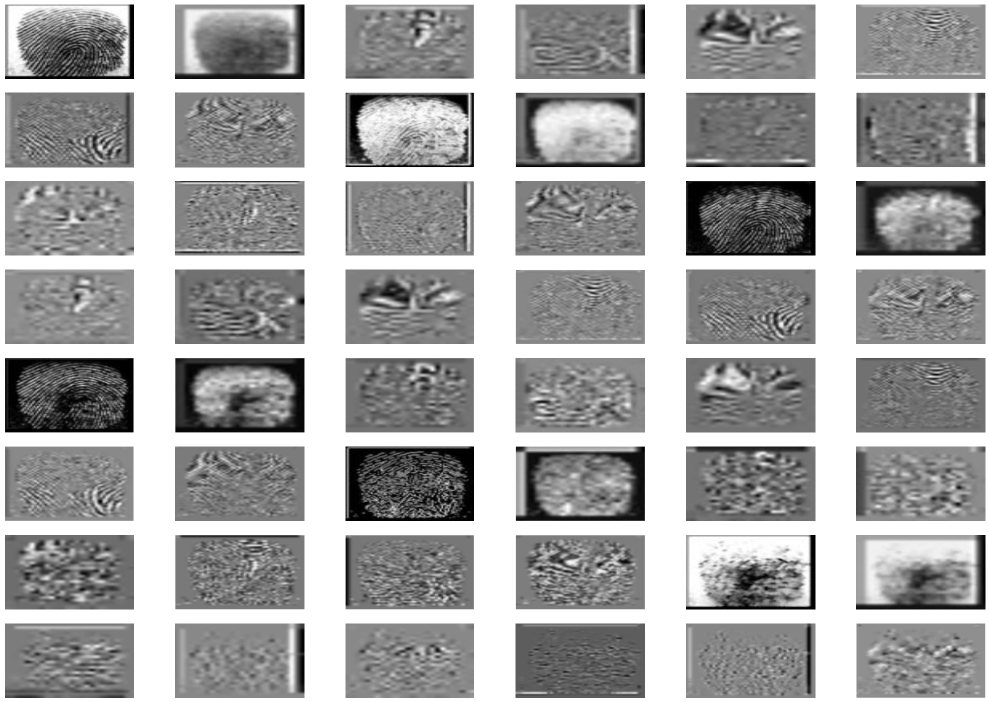

Figure 2: Visualization of the extracted multiscale morphological–wavelet features for a representative fingerprint sample, illustrating the 48 subband feature maps derived from combined morphological operations and discrete wavelet decomposition

3.2 Quantitative Gender Detection Performance

This section assesses performance heuristically based on standard classification measures of the test dataset. To facilitate robust and comprehensive fair assessment, several metrics, including the ROC, confusion matrix, and other standard metrics of accuracy, precision, recall, and F1 score, are aggregated. These capture the model's effectiveness and its applicability based on the class and its level of saturation on metrics.

In figure 4 shows the ROC curves for the test set by the proposed method for both males and females. The ROC curve shows the balance between the true positive and the false positive rates for different values of the score and provides an independent measurement of the overall discrimination power of the classifier. As the figure shows, the curves for both classes move closely towards the top left corner of the plot. The curves indicate the strong discrimination power of the classifier. The area under each ROC curve equals to the AUC and is about 0.99 for both male and female. The proposed method has achieved optimal discrimination between the two classes representing the two genders.

The consistent good AUC values confirm that the developed multistage approach, comprised of morphological enhancement, multiscale wavelet feature extraction, Siamese-based dimensionality reduction, and residual classification, provides very reliable gender prediction results with very little overlap between the distributions of class scores. The close match between the ROC curves for the male and female classes confirms good, unbiased classification performance. The stability of the results under varying decision thresholds further validates the robustness of the learned embeddings and suggests good performance under various operating scenarios typically found in biometric or forensic applications. As further supported by the confusion matrix shown in figure 5, nearly all fingerprints were correctly classified as predicted; all 945 male fingerprints were correctly classified as male and 249 out of 255 female fingerprints were classified correctly. Only 6 female fingerprints were misclassified.

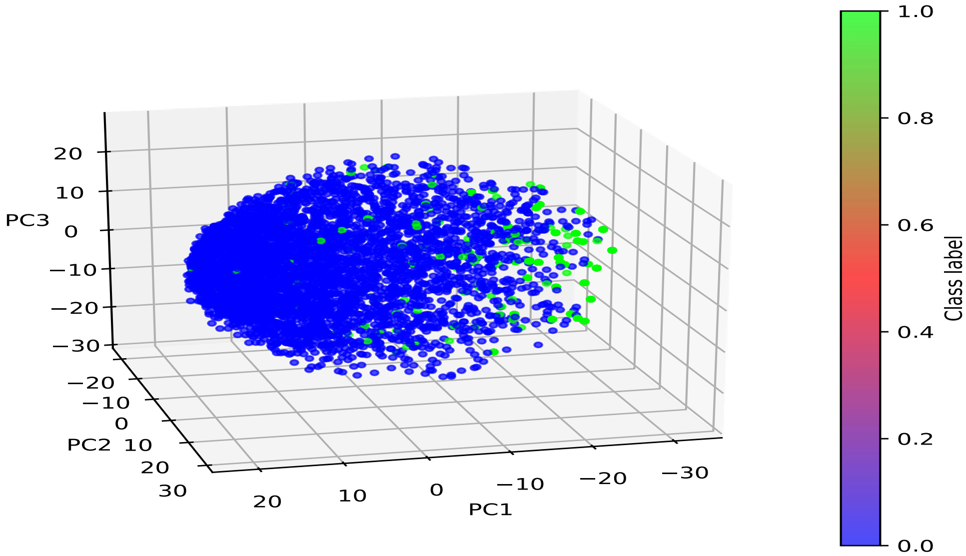

Figure 3: Three-dimensional scatter plot of the learned siamese embedding space visualized along the first three principal components obtained via principal component analysis (PCA)

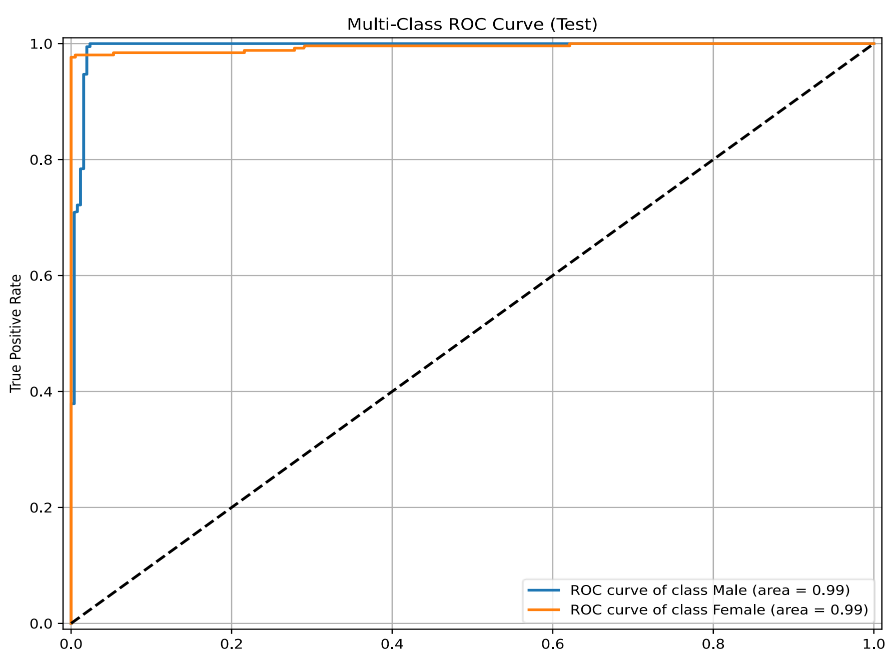

Figure 4: The ROC curve of the gender classification using the proposed method

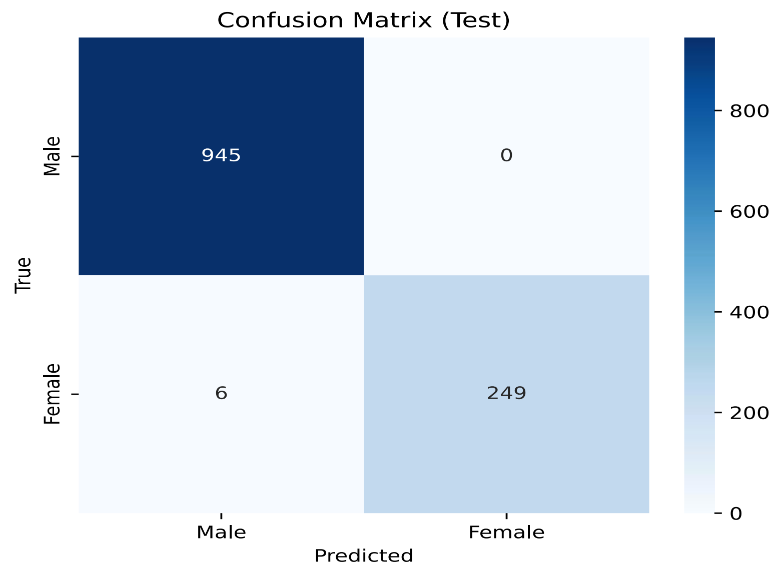

Figure 5: The confusion matrix of gender classification using the proposed method

The classification performance measures in figure 6 further strengthen these results; the system yielded 99.50% accuracy, 99.68% precision, and 98.82% recall. These low numbers for both false positives and false negatives are encouraging, as is the good F1 score which further indicates a consistent system behavior across the full range of decision thresholds. Overall, both the effectiveness of multiscale feature extraction and the robustness of Siamese-based dimensionality reduction are well confirmed by these experimental results for the task of accurate and unbiased gender classification using fingerprints.

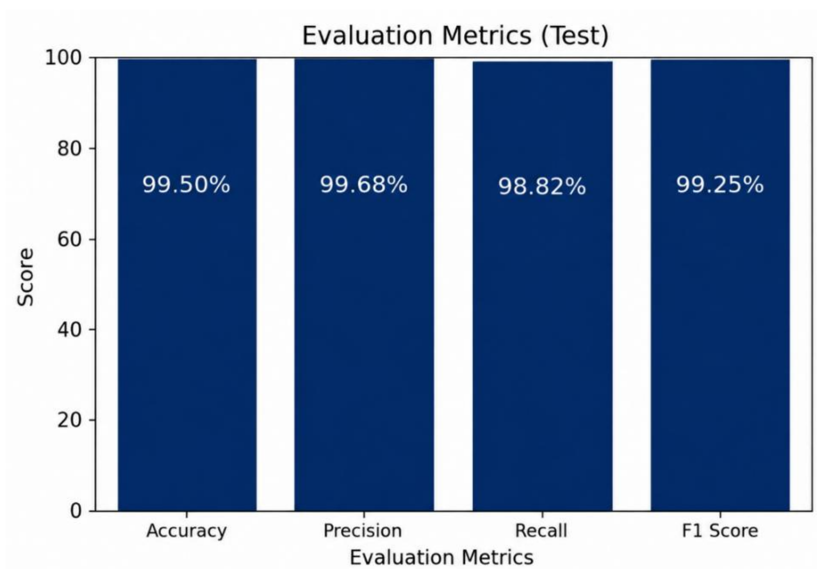

Figure 6: The evaluation metrics bar chart for gender classification using the proposed method

3.3 Ablation Study on Proposed Fingerprint Gender Classification Architecture

In order to test the proposed multi-stage architecture, as well as the validity of the morphological-wavelet feature extraction module, an ablation study was conducted. Two hypotheses are tested with this study:

1. Is the increased architecture complexity justifiable over simple models?, 2. Do the individual morphological operations and wavelets all contribute to the performance improvement? Seven different models are sequentially tested on SOCOFing data to estimate how each part is helping. These seven models include: CNN baseline, CNN + SVM, Morphology + CNN, DWT + CNN, Morphology + DWT + CNN, Morphology+DWT+Siamese compression+CNN, and the complete proposed model with residual-FPN classifier. Three different test conditions were evaluated: original images, Gaussian noise with variance 10, and salt-and-pepper noise with density 3%. Table 1 shows the results.

Table 1: Ablation analysis of model complexity impact on classification performance

Case	Model Variant	Original	Gaussian Noise	Salt & Pepper
1	Simple CNN	98.75	92.67	90.92
2	CNN + SVM	99.00	93.58	91.25
3	Morphology + CNN	99.08	94.08	93.67
4	DWT + CNN	99.16	95.17	94.42
5	Morph + DWT + CNN	99.33	96.33	96.08
6	+ Siamese Compression	99.33	97.42	97.17
7	Full Model	99.50	98.33	97.67

Accuracy obtained in the original images shows that the models have a high accuracy (99.50 % for full architecture). However, when images are corrupted the models have differences. Accuracy drop heavily with Gaussian noise in simple CNN (92.67 %) and CNN + SVM (93.58 %) while with morphology preprocessing, DWT multiscale features, and Siamese compression the performance rises until the full model is 98.33 % accurate. Similar effect appears with salt and pepper noise with full model at 97.67% that proves all the blocks are complementary and robust.

The second part of the ablation study looks at the importance of the individual morphology operator and the mother wavelet. The ridge enhancement operator and skeleton operator cause the biggest drops in performance, whereas top-hat, black-hat, and gradient show smaller drops (Table 2). Trying different mother wavelets confirmed that db2 offers the best performance in terms of localness, smoothness, and efficiency, whereas other Daubechies and Haar perform poorly (Table 3). Both experiments show that the proposed architecture and all of the blocks, plus 48 feature bands, give a very stable and discriminative embedding for gender classification of fingerprints. The proposed fingerprint gender-classification framework also achieves computational scalability for growing databases. With larger data, due to the dimensionality reduction created by the Siamese network, the memory size is small, and the computational complexity is reduced as well. This will allow it to achieve performance in a large number of fingerprint images.

Table 2: Ablation analysis of morphological operators

Ablation Case	Accuracy	F1-Score
Remove top-hat	99.08	98.61
Remove black-hat	99.00	98.48
Remove gradient	98.67	97.97
Remove skeleton	98.17	97.20
Remove ridge-enhancement	97.17	95.63

Table 3: Effect of different mother wavelets

Mother Wavelet	Accuracy	F1-Score
Haar	96.75	94.98
db4	98.08	97.06
db6	98.83	98.23
db12	98.75	98.10
Symlet	99.33	98.99

3.4 Comparison with Existing Model

The described gender detection framework is much more efficient than others. Most methods (e.g., A hybrid CNN-SVM, Serin et al., (2024)) got 99.25% classification accuracy, but those methods did not involve scale-and-frequency domain analysis, so those systems can't fully capture the minute differences in ridges. Although the four-layer CNN and ANN achieved 96.46% accuracy, feature dimensionality reduction, attention mechanism, and multi-scale feature fusion were not included. The proposed approach employs morphological preprocessing combined with multi-scale discrete wavelet analysis and Siamese network-based feature dimensionality reduction, using a residual neural network classifier that comprises an attention mechanism and non-local aggregation for long-range ridge flow feature extraction and learning. The algorithm attained 99.5% classification accuracy. The comparison of the approach and other existing methods in fingerprint-based gender classification can be illustrated as in table 4.

Table 4: Comparison of the proposed fingerprint gender detection framework with recent methods

Reference	Methodology	Dataset	Accuracy (%)
Serin et al., (2024)	CNN-SVM	SOCOFing dataset	99.25
Maiti & Basak, (2023)	Four-layer Convolutional Neural Network	SOCOFing dataset	96.46
Proposed method	Morphology-based preprocessing, Multiscale Discrete Wavelet Transform Analysis, A Siamese Network, Residual Neural Network Classifier	SOCOFing dataset	99.5

3.5 Limitations

The proposed fingerprint gender-classification system performs well with high accuracy and robustness, but depends on high-quality gray-scale fingerprint images. High noise and missing prints might pose difficulty to the classification system. Scalability to large datasets and real-time applications in limited hardware has not been explicitly verified, and adversarial robustness is yet to be studied.

4 Conclusion

This work proposes a novel multiscale residual framework for gender classification based on fingerprint images which demonstrates high performance and accuracy in discriminating subtle sex related features from fingerprint images. Integrating morphological preprocessing, multiscale feature extraction using discrete wavelet transform and dimensionality reduction by a Siamese network based classifier and residual neural network, effectively extract the global, mid and fine-grained ridge patterns of fingerprints. Tested over the SOCOFing database, the proposed framework achieves the excellent statistical results of overall accuracy, precision, recall and AUC as 99.50%, 99.68%, 98.82% and 0.99 for male and female classes, respectively. Through ablation study, the benefits brought by the morphological operators, the wavelet subbands and the Siamese compression are clearly evidenced, while through robustness tests under Gaussian and salt and pepper noise, only minimal degradation has been observed. Comparison of performances shows the multiscale, frequency-awareness strategy works better than prior models like CNN-SVM and simple CNN which makes the subtle gender specific ridge characteristics successfully identified with discriminative power kept under noisy environment.

Although achieving high performance, there are limitations such as the usage of clear grayscale fingerprint images, and unknown scalability under harsh hardware resource constrains and real time operation environments need further tested and proved. And the framework hasn't been examined under adversarial condition and the corrupted fingerprints with missing or occlusion parts of them. In the future, extending the method towards cross dataset generalization, adding adversarial training to secure more effectively, researching light weight architectures for embedded biometrics, using adaptive attention mechanisms and multi-modal biometric fusion could further improve performance in complicated operational conditions. Overall, the proposed framework presents a scalable, accurate, and robust method of automatic fingerprint-based gender classification that could be used for forensics applications, biometric identification systems, and large-scale deployment in varied operational scenarios.

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