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Analysis of Fingerprint Features: Ridge Information, Minutia Information and DWT Features for the Design of Gender Classifier Clusters

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Abstract. Fingerprints offer a unique and incommutably into an existent's identity, including their gender. This paper introduces a method for gender identification using fingerprint features, including ridge information, minutiae information, and six-level discrete wavelet transform (DWT). The method was evaluated on a dataset of 100 individuals, with 50 male and 50 female samples. The proposed method first extracts the three features from the fingerprint images. Ridge information includes the minimum, maximum, and average ridge length. Minutiae information includes the ridge end count, ridge bifurcation count, and total ridge count. Six-level DWT is used to extract frequency features from the fingerprint images. Next, the features are clustered finger-wise into minimum, maximum, and average values for the male and female classes. These finger-wise clusters are then used to design a classifier for male and female. The proposed method achieved an accuracy of 88.28% for gender identification on the database of 100 individuals. The right ring finger was the most accurate finger for gender identification, with an accuracy of 95.46%. This simple and effective method for fingerprint-based gender identification achieved an accuracy of 88.28% on the database of 100 individuals. The method can be further improved by using a larger database and by extracting more features from the fingerprint images.

Keywords: *Analysis, Fingerprint, Features, Ridge, Minutia, Discrete wavelet transform, DWT, Gender, Classification, Clusters.*

1 Introduction

Gender identification is a crucial aspect of automated human authentication biometric systems, with applications in forensics and secure authentication. Various biometric modalities, including fingerprints, blood, irises, gait, and body shape, are commonly employed for gender recognition. Recent research indicates that fingerprint images can also serve as reliable identifiers for individuals. Forensic authorities utilize fingerprint images to determine a person's gender based on characteristic features within these images. Despite limited studies on gender identification from fingerprint images in the past decade, this research proposes that fingerprint patterns exhibit distinct variations between male and female categories.

To investigate this premise, an internal dataset of 1000 fingerprint images from 100 individuals was assembled. The dataset comprises 500 samples from male individuals and 500 samples from female individuals, each contributing 10 fingerprint images per person. These samples were captured using an optical USB 1.1 fingerprint scanner, the Nitgen Fingkey Hamster, as depicted in Figure 1.

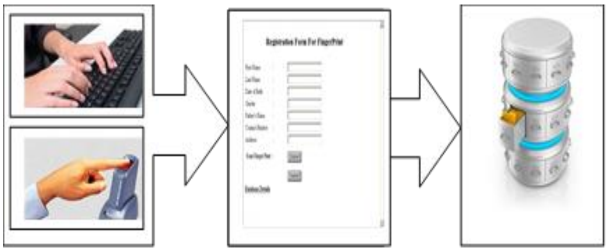

Fig-1: Fingerprints are acquired real time

Subsequent to their collection, the fingerprint images undergo image processing techniques such as segmentation, orientation determination, binarization, thinning, and minutiae extraction to generate five distinct image categories. These preprocessing steps are crucial for enhancing the fingerprint image quality, which in turn

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improves the accuracy of feature extraction from these images. The impact of image preprocessing is evident in the distinct types of results depicted in Figure 2.

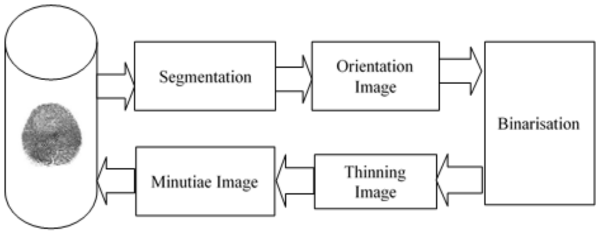


Fig 2. Fingerprint image quality enhancement steps.

The results of the fingerprint image enhancements are as shown in Figure 3 below,

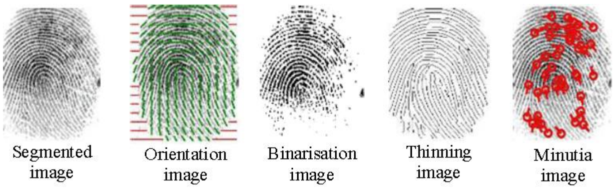


Fig 3. Result of fingerprint image enhancement.

Enhanced fingerprint images serve as the foundation for extracting the diverse features that characterize fingerprint patterns. This research focuses on three primary categories of features: ridge features, minutiae features, and texture features. Ridge features are defined by the continuous parallel ridges and valleys that form the fingerprint's visible pattern. Minutiae features, on the other hand, are specific points on the ridges, such as ridge endings and bifurcations, that provide unique identifiers for individual fingerprints. Texture features capture the overall spatial distribution of ridges and valleys, providing additional information for fingerprint recognition,

Discrete Wavelet Transform: The frequency domain feature vector is extracted from the segmented fingerprint image using a six-level two-dimensional discrete wavelet transform (2D DWT) decomposition. The energy of the feature vector is calculated using the formula:

$$\text{Energy} = \sum_{i,j=1}^{N} c^2\,(\mathrm{i},\mathrm{j}) \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1)$$

- **Ridge Information:** The ridge features of each image are characterized by the total number of ridges, the minimum ridge length, the maximum ridge length, and the average ridge length.

- **Minutia Information:** The minutia information of each image is found with ridge end count ridge bifurcation count, total ridge bifurcation count features.

The next step is to combine these three feature vectors together in to a single combined vector, which will be stored in database for classification as shown in Figure 4

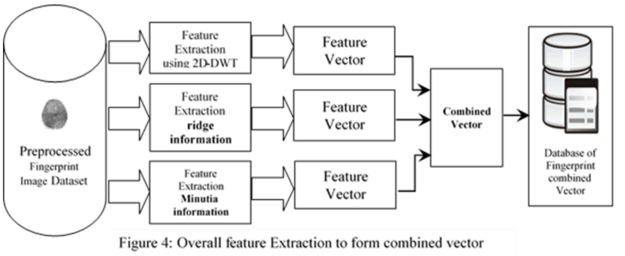


Fig 4. Overall feature extraction to form combined vector

2 Literature Reviews

Fingerprint gender classification has been an active research area for many years. Researchers have proposed a variety of methods for extracting features from fingerprints and using these features to classify gender. Some of the most common features used include ridge thickness, ridge density, minutiae, and wavelet transform coefficients.

Ashish Mishra et al. [22] compared the results of classification by two classifiers, Naïve Bayes and SVM. They found that SVM outperformed Naïve Bayes in terms of accuracy. Sri Suwarno et al. [4] compared the features wavelet transform and ridge density counting in classification and showed that DWT gives some advantages.

Eyüp Burak CEYHAN et al. [17] used a database of 600 fingerprints, 300 from males and 300 from females. They divided the database into two parts, 66% for training and 34% for testing. They used a variety of features, including ridge thickness, ridge density, and minutiae, and they obtained an accuracy of 92%.

Ronny Merkel et al. [2] applied features to intensity as well as topography data of the time series, leading in best cases to a large amount of correlation coefficients greater than 0.8 and to kappa classification performances between 0.51 and 0.85. Prabha et al. [3] used back propagation neural network outperformed in gender identification task and has given the accuracy of 96.60%.

A. S. Falohun et al. [10] used a database of 140 fingerprints, 70 males and 70 females. They extracted the Ridge Thickness Valley Thickness Ratio (RTVTR) features and used them to train a support vector machine (SVM) classifier. They obtained an accuracy of 95%.

Shivanand Gornale et al. [11] worked on a database of 370 male and 370 female fingerprints. They extracted features from the fingerprints using wavelet transform and used them to train linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) classifiers. They obtained accuracies of 92% and 93%, respectively.

Himanshi et al. [12] showed that the previous methods on feature analysis are robust against gradient deviations. Suchita Tarare et al. [14] proposed a system that worked on a dataset of 1000 male and 1000 female fingerprints. They used a K-nearest neighbor (KNN) classifier with Euclidean distance measure for classification. They obtained an accuracy of 94%.

Mangesh K. Shinde et al. [15] used an internal database of 1000 fingerprints, 500 male and 500 female. They extracted features from the fingerprints using ridge thickness and ridge density, and they used these features to train a support vector machine (SVM) classifier. They obtained an accuracy of 93%.

Suman Sahu et al. [16] used a database of 550 male and female fingerprints. They extracted features from the fingerprints using ridge valley area (RVA) and frequency domain analysis. They used these features to train an adaptive neuro-fuzzy inference system (ANFIS) classifier. They obtained an accuracy of 92%.

D.Gnana Rajesh et al. [18] used a database of 180 fingerprints, 80 female and 100 male. They extracted features from the fingerprints using discrete wavelet transform (DWT) and used these features to train a Gaussian mixture model (GMM) classifier. They obtained an accuracy of 93%.

Ms.Bindhu K. Rajan et al. [19] extracted features from both iris and fingerprint images and used these features to train a neural network. They obtained an accuracy of 95%.

P. Gnanasivam et al. [20] used an internal database of 3570 fingerprints, 1980 male and 1590 female. They extracted features from the fingerprints using wavelet transform and used these features to train a support vector machine (SVM) classifier. They obtained an accuracy of 94%.

Yi-Pin Hsu et al. [5] used an SVM classifier to classify fingerprints based on ridge endings and ridge bifurcation types. They obtained an accuracy of 92%.

Unhale A.A et al. [13] proposed a new matching scheme using a breadth-first search (BFS) to detect the matched minutiae pairs. They compared the results of their proposed ridge features and conventional minutiae features with the novel matching scheme. They found that their proposed method outperformed the conventional method in terms of accuracy.

Ritu Kaur et al. [9] proposed a method for gender estimation using fast Fourier transform (FFT), discrete cosine transform (DCT), and power spectral density (PSD) features extracted from fingerprint images. They achieved an accuracy of 87.5% on their dataset.

Samta Gupta et al. [8] employed wavelet transformation to extract fingerprint characteristics and achieved an accuracy of 86.2% using Naïve Bayes classifier.

Heena Agrawal et al. [7] used features such as ridge thickness, ridge density, and valley thickness to valley thickness ratio (RTVTR) to estimate gender from fingerprints. They achieved an accuracy of 84.5% using Support Vector Machine (SVM) classifier.

Rijo Jackson Tom et al. [6] proposed a method using 2D-Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) features to extract gender information from fingerprints. They achieved an accuracy of 87.2% using SVM classifier.

Preeti Maheshwary et al. [23] trained a Naïve Bayes classifier with fingerprint data and achieved an accuracy of 85.8% for gender estimation.

Proper analysis of fingerprint features is crucial for accurate gender classification. Pre-analysis of feature values provides several advantages, including designing classifiers with appropriate feature ranges, facilitating decision tree implementations in neural network-based classifiers, enhancing understanding during the testing phase, and improving accuracy. While fingerprint feature extraction methods are precise and powerful, achieving accurate gender classification hinges on thorough analysis of these features. Therefore, emphasizing research on the analysis of fingerprint-extracted features is essential for achieving accurate gender classification results.

3 Methodology Used

Fingerprint feature extraction is a critical step in the proposed automated gender classification system. In this research, two main methodologies were employed for fingerprint feature extraction:

3.1 Discrete Wavelet Transform (DWT):

The Discrete Wavelet Transform (DWT) is a powerful tool for feature extraction in fingerprint recognition. It offers several advantages over traditional Fourier-based methods, including the ability to capture both frequency and location information. In this work, DWT is employed to extract features from fingerprint images using the Daubechies-tab 4 filter and the Mallat-tree decomposition algorithm.

The DWT decomposes the original fingerprint image into a series of sub-bands, each representing a different frequency range. The sub-bands are logarithmically spaced in frequency, corresponding to octave-band decomposition. The first level of decomposition produces four sub-bands: LL1, LH1, HL1, and HH1 as shown in Figure 5(a). LL1 represents the coarse-level coefficients, or approximation image, while LH1, HL1, and HH1 represent the fine-scale coefficients, or detail images.

To obtain a more detailed representation of the fingerprint, the sub-band LL1 is further decomposed using DWT. This results in a two-level wavelet decomposition, as shown in Figure 5(b). The resulting sub-bands are used to extract features that are characteristic of the fingerprint's ridges and valleys.

The DWT-based feature extraction method has been shown to be effective in various fingerprint recognition tasks, including minutiae extraction, fingerprint matching, and fingerprint classification.

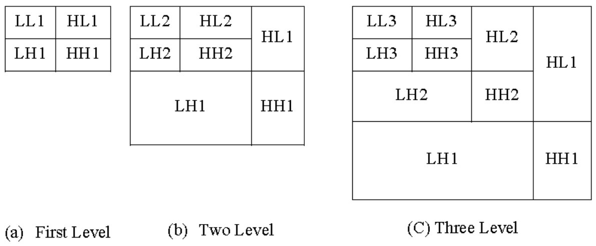


Fig-5 fingerprint image decomposition structure

To achieve a six-level wavelet decomposition, the LL2 image from the previous iteration is used as the input for the next level of decomposition, as shown in Figure 5(c). This process continues until the desired level of decomposition is reached. The detailed sub-bands of the decomposed images are extracted as features for fingerprint gender classification. These features, derived from the wavelet-transformed images, are utilized to effectively distinguish between male and female fingerprints.

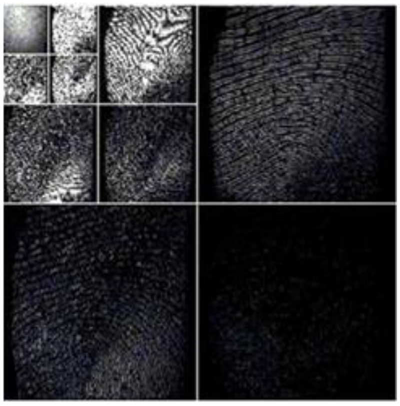


Fig 6 Decomposition of thumb image up to six-Level

Following Table 1 represents the extracted DWT features values for all six levels for ten fingers of a person,

Table 1. Energy levels at various levels of DWT of a person fingerprint

Finger Name	DWT L1	DWT L2	DWT L3	DWT L4	DWT L5	DWT L6
Left Thumb	1551.65	7.82	3.91	2.22	1.55	2.81
Left Index Finger	1574.00	19.00	9.50	3.00	1.11	0.37
Left Middle Finger	1567.60	15.80	7.90	2.95	1.00	0.41
Left Ring Finger	1589.65	26.82	13.41	6.90	3.29	3.04
Left Little Finger	1555.44	9.72	4.86	5.48	3.34	2.82
Right Thumb	1536.00	0.00	0.00	10.44	6.76	6.67
Right Index Finger	1536.00	0.00	0.00	0.00	0.00	0.00
Right Middle Finger	1583.98	23.99	11.99	4.31	1.53	0.59
Right Ring Finger	1594.73	29.36	14.68	4.31	1.46	0.51
Right Little Finger	1599.98	31.99	15.99	4.26	1.19	0.63

3.2 Ridge Information:

Fingerprints are unique patterns formed by friction ridges (elevated) and furrows (depressed) on the pads of the fingers and thumbs. These ridges and furrows are created by the underlying dermal papillae, which remain unchanged despite superficial injuries such as burns, abrasions, or cuts. As a result, any new skin that grows will retain the original fingerprint pattern. However, deeper injuries that damage the dermal papillae can permanently erase the ridges, eliminating the fingerprint. Friction ridge patterns are categorized into three main types: arches, loops, and whorls, each with distinct variations based on the shape and arrangement of the ridges. As shown in figure below Figure 7.

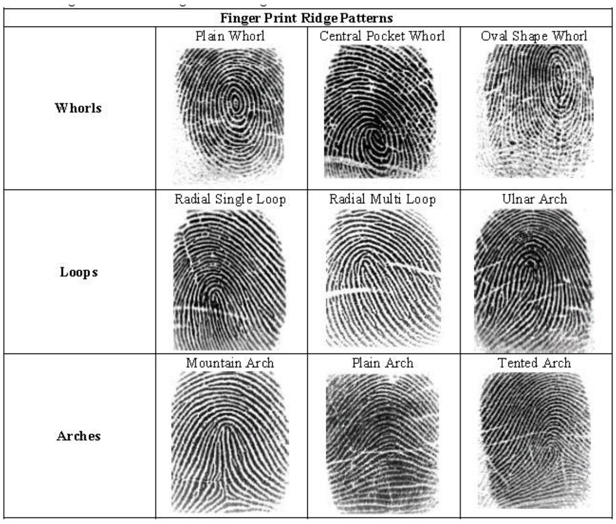


Fig 7. Three pattern types of fingerprint.

In our research, we have developed an algorithm that extracts ridge features from fingerprints. These features include ridge count (RC), ridge length (RL), minimum ridge length (Min-RL), maximum ridge length (Max-RL), sum of all ridge lengths (Sum-RL), and average ridge length (Avg-RL). Table 2 shows the ridge features extracted for ten fingers of a person.

```
Algorithm Calculate_Ridge_Information:
   Input: Fingerprint image P(x, y) of size 256x256
   Initialize variables:
   RC = 0          // Ridge Count
   RL = 0          // Ridge Length
   Min-RL = ∞   // Minimum Ridge Length (initialized to positive infinity)
   Max-RL = 0   // Maximum Ridge Length (initialized to zero)
   Sum-RL = 0   // Sum of all Ridge Lengths
   Avg-RL = 0    // Average Ridge Length
     For x = 1 to 256 step 1
       For y = 1 to 256 step 1
         if (P(x, y) == BLACK) then
           // Start tracing the ridge
           RC = RC + 1 // Increment Ridge Count
           RL = 0   // Reset Ridge Length of new ridge
           // Trace the ridge until it terminates
           while (P(x, y) == BLACK)
             Set P(x, y) = WHITE
             RL = RL + 1 // Increment Ridge Length
             // Move to the next pixel in the ridge
             // (Assuming 8-connected neighbours)
             if (P(x - 1, y - 1) == BLACK) then
               x = x – 1 and   y = y - 1
             else if (P(x, y – 1) == BLACK) then
               y = y - 1
             else if (P(x + 1, y – 1) == BLACK) then
               x = x + 1 and   y = y – 1
             else if (P(x – 1, y) == BLACK) then
               x = x – 1
             else if (P(x + 1, y) == BLACK) then
               x = x + 1
             else if (P(x – 1, y + 1) == BLACK) then
               x = x – 1 and   y = y + 1
             else if (P(x, y + 1) == BLACK) then
               y = y + 1
             else if (P(x + 1, y + 1) == BLACK) then
               x = x + 1  and   y = y + 1
           End while
         if (RL < Min-RL) then // Update Min-RL & Max-RL
             Min-RL = RL
         end if
         if (RL > Max-RL) then
             Max-RL = RL
           end if
           Sum-RL = Sum-RL + RL     // Update Sum-RL
         end if
       Next y
   Next x
   if (RC > 0) then
       Avg-RL = Sum-RL / RC      // Calculate Average Ridge Length
   else
       Avg-RL = 0
   end if
   Store  RC, RL, Min-RL, Max-RL, Sum-RL, Avg-RL
   // Output the calculated Ridge Information features
End of Algorithm
```

Fig 8. Algorithm for ridge feature information extraction.

Table 2 the ridge features extracted for ten fingers of a person,

Finger Name	Max-RL	Min-RL	Avg-RL	RC
Left Thumb	14.42	1.43	5.17	189
Left Index Finger	16.61	1.94	5.18	178
Left Middle Finger	13.27	2.96	4.18	180
Left Ring Finger	16.85	2.38	6.17	186
Left Little Finger	17.25	1.07	5.22	144
Right Thumb	16.51	1.08	5.16	205
Right Index Finger	12.87	1.86	4.18	176
Right Middle Finger	14.06	1.46	5.19	167
Right Ring Finger	14.75	1.24	4.22	140
Right Little Finger	14.42	2.22	5.20	159

3.3. Minutia Information:

Minutiae points serve as crucial features within a fingerprint image, playing a pivotal role in fingerprint identification. They are instrumental in determining the distinctiveness of a fingerprint by marking locations where the ridge lines either terminate or bifurcate. These minutiae points essentially represent local discontinuities in the ridge patterns and manifest in various forms. The primary types of minutiae include ridge endings, where the ridge lines conclude, and ridge bifurcations, where the ridges split into two distinct paths. The uniqueness of a fingerprint image is intricately linked to the specific arrangement and distribution of these minutiae points. The identification and analysis of minutiae not only contribute to the accuracy of fingerprint recognition systems but also underscore the individuality inherent in each fingerprint, making them a fundamental aspect of forensic and biometric applications.

- **Core:** Indicating the onset of a loop, the core marks the point where a ridge undergoes a sudden change in orientation.
- **Short Ridge:** Characterized by an abrupt start and end in orientation, short ridges contribute to the minutiae landscape.
- **Ending Ridge:** Signifying the abrupt termination of a ridge, an ending ridge adds to the distinctive features of a fingerprint.
- **Bifurcation Ridge or Fork:** Occurring where a single ridge branches into two or more, bifurcation points contribute to the fingerprint's unique pattern.
- **Delta:** Representing a sudden change in orientation, typically forming a tented arch, the delta is a key minutia point.
- **Ridge Hook:** Found where a ridge briefly bifurcates, ridge hooks add complexity to the minutiae structure.
- **Eye:** Points where a short ridge connects with an arching ridge, known as eyes, further contribute to the minutiae landscape.
- **Ridge Dots:** Small ridges within a fingerprint, ridge dots enhance the overall pattern complexity.
- **Ridge Islands:** Slightly longer than dots and situated between diverging ridges, islands contribute to the minutiae features.
- **Crossovers:** Points where two ridges intersect, forming crossovers that are distinctive features in fingerprint analysis.
- **Bridges:** Small ridges connecting two longer adjacent ridges, bridges add to the intricacy of the fingerprint pattern.
- **Enclosures:** Ridge points where the eye is filled with a dot or island ridge are referred to as enclosures, contributing to the minutiae characteristics.
- **Ponds or Lakes:** Empty spaces between diverging ridges, ponds or lakes are integral to the overall minutiae structure.
- **Spurs:** Notches protruding from a ridge, spurs contribute to the detailed minutiae landscape within a fingerprint.

Each minutiae type plays a unique role in shaping the fingerprint's distinct pattern, facilitating accurate identification in forensic and biometric applications. The states for the ridges in the above mentions ridge patterns are different, as shown in Figure 9.

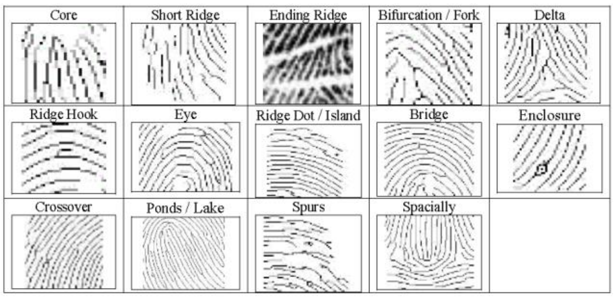


Fig 9. Overall ridge states in ridge pattern.

Ridge endings and ridge bifurcations are the most commonly used minutia types since all other types of minutiae are based on a combination of these two types. Following figure 9 shows common steps of algorithm for minutiae patterns like Ridge bifurcation count(RBC), Ridge end count (REC), Minutia count (μC).

```
Algorithm MinutiaInformationExtraction:
    Input: Fingerprint image P(x, y) of size MxN
    Initialize variables:
    MinutiaCount = 0
    BifurcationCount = 0
    RidgeEndCount = 0
    For x = 1 to M step 1
        For y = 1 to N step 1
            if (P(x, y) == BLACK) then
                // Check for ridge endings and bifurcations
                if (IsRidgeEnd(P, x, y)) then
                    RidgeEndCount = RidgeEndCount + 1
                end if
                if (IsBifurcation(P, x, y)) then
                    BifurcationCount = BifurcationCount + 1
                end if
                // Increment total minutia count
                MinutiaCount = MinutiaCount + 1
            end if
        Next y
    Next x
    // Output the extracted Minutia Information
    Store MinutiaCount, BifurcationCount,
RidgeEndCount
End Algorithm
Function IsRidgeEnd(P, x, y):
    // Check if the pixel (x, y) is a ridge ending point
    // (Assuming 8-connected neighbors)
    count = 0
    for i = x - 1 to x + 1
        for j = y - 1 to y + 1
            if (P(i, j) == BLACK) then
                count = count + 1
            end if
        Next j
    Next i
    return (count == 2) // A ridge end should have only
two black neighbours
End Function
Function IsBifurcation(P, x, y):
    // Check if the pixel (x, y) is a ridge bifurcation
point
    // (Assuming 8-connected neighbors)
    count = 0
    for i = x - 1 to x + 1
        for j = y - 1 to y + 1
            if (P(i, j) == BLACK) then
                count = count + 1
            end if
        Next j
    Next i
    return (count >= 4) // A ridge bifurcation should
have at least four black neighbors
End Function
```

Fig 9. Algorithm for minutia feature information extraction.

Table 3 the minutia features extracted for ten fingers of a person

Finger Name	Minutia Count	Bifurcation count	Ridge end count
Left Thumb	41	3	38
Left Index Finger	53	11	42
Left Middle Finger	28	6	22
Left Ring Finger	50	5	45
Left Little Finger	53	5	48
Right Thumb	47	6	41
Right Index Finger	53	4	49
Right Middle Finger	39	5	34
Right Ring Finger	86	6	80

Right Little Finger	60	5	55

4 Data Set

In this research proposal, we have meticulously compiled a comprehensive internal prime dataset comprising fingerprint images obtained from 100 individuals, encompassing all ten fingers of each participant. The dataset is distinctly structured with 500 samples from male individuals, each contributing scans from all ten fingers, and an equivalent set of 500 samples collected from female participants. The fingerprint acquisition process utilized the state-of-the-art Fingkey Hamster II scanner, a product of Nitgen Biometric Solutions based in Korea. Consequently, our internal dataset comprises a total of 1000 samples, offering a robust and diverse collection for our research endeavors.

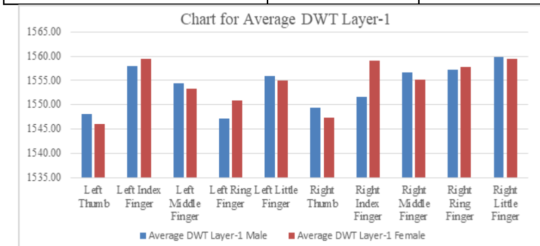
The fingerprint data in our internal database is derived from individuals spanning various age groups, ensuring a representative and inclusive dataset. Notably, the collection process prioritized flexibility by capturing fingerprints without imposing any restrictions on hand position, pressure applied to the scanner, or specific orientations, as highlighted in reference [21]. This approach aims to enhance the authenticity and variability of the dataset, making it well-suited for a broad spectrum of analyses and investigations in the domain of fingerprint research.

5 Results and Analysis

In the gender classification analysis of the ten fingers based on the collected 100 samples for 50 male and 50 Female, minimum and maximum values, as well as average values, for each feature have been meticulously examined. In instances where testing feature vectors exhibit overlaps, average values have been computed using minimum distance formulas. The summarized ranges or clusters of male and female feature values are presented in Table 4, specifically focusing on DWT Layer 1. This table provides a consolidated view of the distinct ranges associated with male and female classifications for each finger. The comprehensive analysis aims to discern patterns and variations in DWT Layer 1 features across the ten fingers, contributing valuable insights to the gender classification methodology.

Table 4: DWT Layer 1 summarized values
10 fingers of male and female samples

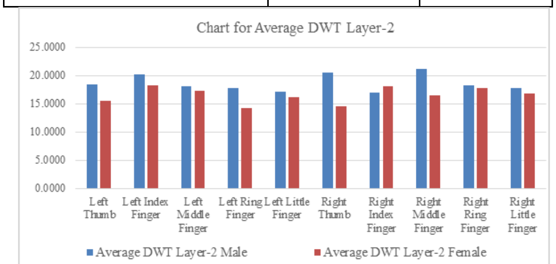
Finger Name	Male	Female
Left Thumb	1548.03	1546.08
Left Index Finger	1557.96	1559.39
Left Middle Finger	1554.44	1553.23
Left Ring Finger	1547.11	1550.96
Left Little Finger	1555.98	1554.96
Right Thumb	1549.37	1547.39
Right Index Finger	1551.55	1559.17
Right Middle Finger	1556.74	1555.19
Right Ring Finger	1557.31	1557.78
Right Little Finger	1559.89	1559.40



For both males and females, the DWT Layer 1 feature values show a consistent pattern across different fingers. The average values exhibit comparable trends. Generally, there is no significant disparity in the DWT Layer 1 feature values between males and females. The differences observed are within a relatively narrow range, suggesting that DWT Layer 1 may not exhibit pronounced gender-related variations. Following Table 5 represents the summarized DWT layer 2 values of the ten finger for 50 male and 50 Female s,

Table 5: DWT Layer 2 summarized values
10 fingers of male and female samples

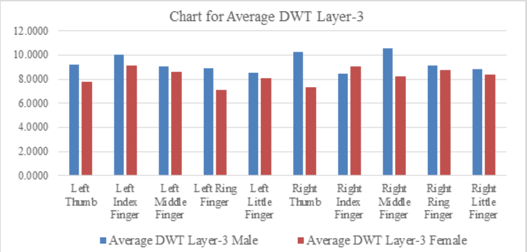
Finger Name	Male	Female
Left Thumb	18.3993	15.5412
Left Index Finger	20.2697	18.3064
Left Middle Finger	18.0748	17.2320
Left Ring Finger	17.7788	14.1740
Left Little Finger	17.1265	16.2504
Right Thumb	20.4743	14.6454
Right Index Finger	16.9588	18.1309
Right Middle Finger	18.3993	15.5412
Right Ring Finger	20.2697	18.3064
Right Little Finger	18.0748	17.2320



The above table appears to represent data for a feature called average DWT Layer 2 measured across different fingerprints and genders. Clear differences between male and female values are observed across all fingerprint categories for DWT Layer 2. In general, male values are higher than female values, except the right index finger value. The Average DWT layer 2 value for right index finger value for female is higher than the male value. Also in the Thumb and Middle Finger, the right-hand values are relatively higher for males. Following Table 6 represents the average DWT layer 3 values of the ten fingers for 50 male and 50 Female,

Table 6: Average DWT Layer 3 values 10 fingers of male and female samples

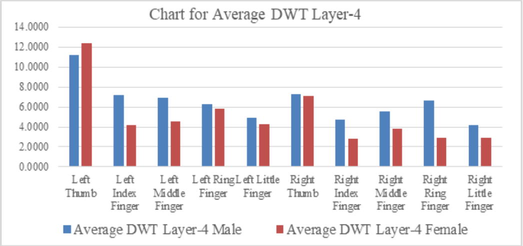
Finger Name	Male	Female
Left Thumb	9.1997	7.7706
Left Index Finger	10.0747	9.1532
Left Middle Finger	9.0374	8.6160
Left Ring Finger	8.8894	7.0870
Left Little Finger	8.5632	8.1252
Right Thumb	10.2371	7.3227
Right Index Finger	8.4794	9.0655
Right Middle Finger	10.5882	8.2227
Right Ring Finger	9.1342	8.7652
Right Little Finger	8.8679	8.3605



In analyzing the provided data for the feature "Average of DWT Layer 3" across different fingerprints and genders, the conclusions can be drawn, similar to the previous feature (DWT Layer 2), there are noticeable differences between male and female values. In general, male values are higher than female values across all fingerprint categories for DWT Layer 3. Also Similar to DWT Layer 2, there may be a pattern of asymmetry between left and right hands for certain fingerprint categories. For example, in the Thumb and Middle Finger, the right-hand values are relatively higher for males. Following Table 7 represents the average DWT layer 4 values of the ten fingers for 50 male and 50 Female,

Table 7: Average DWT Layer 4 values 10 fingers of male and female samples

Finger Name	Male	Female
Left Thumb	11.2680	12.4443
Left Index Finger	7.2424	4.1878
Left Middle Finger	6.8943	4.5351
Left Ring Finger	6.2615	5.8470
Left Little Finger	4.9391	4.2445
Right Thumb	7.2866	7.0726
Right Index Finger	4.7721	2.8509
Right Middle Finger	5.6027	3.7972
Right Ring Finger	6.6189	2.8783
Right Little Finger	4.2045	2.9070

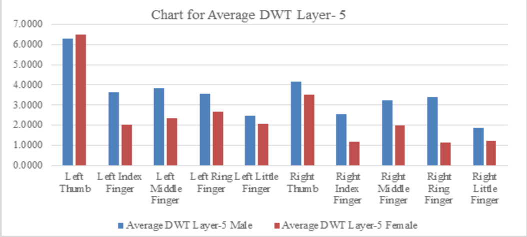


Unlike the previous DWT layers, average DWT Layer 4 shows significant variability across both fingers and gender. The values exhibit a wide range of differences, indicating distinct patterns for each fingerprint category and gender. Male and female values diverge noticeably, with some male values being higher and others lower than their female counterparts. This contrasts with the more consistent patterns observed in the earlier DWT layers. Each fingerprint category demonstrates its own unique trend in DWT Layer 4 values. For instance, the left thumb values is considerably higher for females than males, while all the other fingers shows opposite trend. Following Table 8 represents the summarized DWT layer 5 values of the ten fingers of 50 male and 50 Female,

Table 8: DWT Layer 5 summarized values 10 fingers of male and female samples

Finger Name	Male	Female
Left Thumb	6.3154	6.4983
Left Index Finger	3.6393	2.0377
Left Middle Finger	3.8222	2.3389
Left Ring Finger	3.5580	2.6819
Left Little Finger	2.4572	2.0523
Right Thumb	4.1694	3.4991
Right Index Finger	2.5444	1.1908

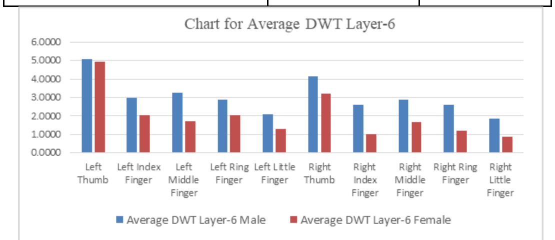
Right Middle Finger	3.2319	1.9734
Right Ring Finger	3.3987	1.1370
Right Little Finger	1.8737	1.2120



DWT Layer 5 values generally show consistent trends across different fingers within each gender. There is a noticeable decrease in values from the Thumb to the Little Finger for both males and females. Unlike DWT Layer 4, the patterns between left and right hands are more consistent. In most cases, the Thumb and other fingers on the left hand have higher values for both males and females. Also the left thumb values is considerably higher for females than males, while all the other fingers shows opposite trend.Following Table 9 represents the summarized DWT layer 6 values of the ten fingers of 50 male and 50 Female,

Table 9: DWT Layer 6 summarized values 10 fingers of male and female samples

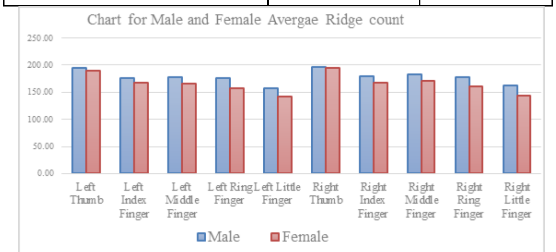
Finger Name	Male	Female
Left Thumb	5.0716	4.9362
Left Index Finger	2.9543	2.0575
Left Middle Finger	3.2536	1.7277
Left Ring Finger	2.8907	2.0447
Left Little Finger	2.0683	1.2746
Right Thumb	4.1259	3.1902
Right Index Finger	2.5894	1.0287
Right Middle Finger	2.8998	1.6691
Right Ring Finger	2.6061	1.1790
Right Little Finger	1.8361	0.8764



DWT Layer 6 values exhibit consistent decreasing trends from the Thumb to the Little Finger within each gender. Male values are consistently higher than female values across all fingerprint categories, suggesting a gender-specific pattern in this DWT layer. The Little Finger consistently has the lowest values, highlighting unique characteristics in relation to DWT Layer 6 for both genders. Following Table 10 represents the summarized Total Ridge count values of the ten fingers of 50 male and 50 Female,

Table 10: Average Total Ridge count summarized values 10 fingers of 50 male and 50 female samples

Finger Name	Male	Female
Left Thumb	193.96	189.27
Left Index Finger	176.85	168.33
Left Middle Finger	177.22	165.61
Left Ring Finger	175.73	157.19
Left Little Finger	157.83	141.28
Right Thumb	197.00	194.33
Right Index Finger	179.58	167.53
Right Middle Finger	182.18	170.17
Right Ring Finger	178.63	161.19
Right Little Finger	161.98	143.58

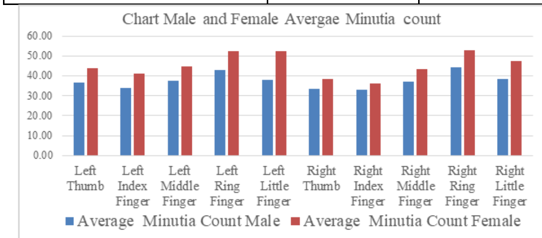


The average ridge count generally follows a decreasing trend from the Thumb to the Little Finger within each gender. This aligns with typical anatomical expectations in fingerprint patterns. Male ridge counts are consistently higher than female ridge counts across all fingerprint categories, reflecting a well-established pattern of higher ridge counts in males. The average ridge count patterns between left and right hands, generally the right hand having slightly higher ridge counts values for both males and females, than the left hands values. Following Table 13 represents the Average Minutia count values of the ten fingers for 50 male and 50 Female,

Table 13: Average Minutia count summarized values 10 fingers

Finger Name	Male	Female
Left Thumb	36.79	43.92
Left Index Finger	33.88	41.03
Left Middle Finger	37.57	44.83
Left Ring Finger	42.94	52.39

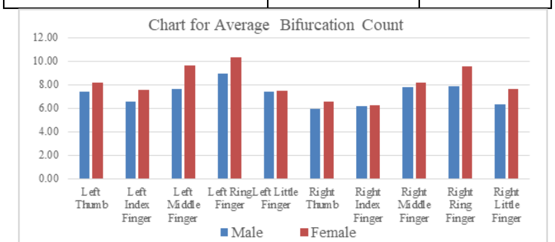
Left Little Finger	38.23	52.25
Right Thumb	33.39	38.56
Right Index Finger	33.17	36.33
Right Middle Finger	36.94	43.36
Right Ring Finger	44.46	52.97
Right Little Finger	38.65	47.69



Female Average minutia counts are generally higher than male minutia counts across all fingerprint categories, indicating a gender-specific pattern of more minutiae in female fingerprints. The minutia count patterns between left and right hands are not consistently symmetrical, with some fingers showing higher minutia counts on the left hand and others on the right hand. The consistently higher minutia counts in the Ring Finger highlight the importance of considering specific finger characteristics in minutia analysis. Following Table 14 represents the summarized average Bifurcation Count values of the ten fingers of 50 male and 50 Female,

Table 14: Average Bifurcation Count summarized values 10 fingers

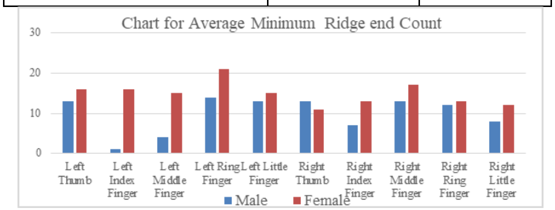
Finger Name	Male	Female
Left Thumb	7.40	8.22
Left Index Finger	6.58	7.53
Left Middle Finger	7.67	9.67
Left Ring Finger	8.92	10.36
Left Little Finger	7.42	7.50
Right Thumb	5.96	6.58
Right Index Finger	6.19	6.22
Right Middle Finger	7.82	8.17
Right Ring Finger	7.83	9.53
Right Little Finger	6.33	7.64



Females generally have higher bifurcation counts than males across all fingerprint categories, indicating a gender-specific pattern of bifurcation distribution. The consistently higher bifurcation counts in the Ring Finger highlight the importance of considering specific finger characteristics in bifurcation analysis for fingerprint identification. Significant variations in bifurcation counts between fingers within the same hand and gender suggest unique characteristics for each finger in terms of bifurcation distribution. The bifurcation count for left hand are relatively higher than the right hand. Following Table 15 represents the summarized average Ridge End Count values of the ten fingers of 50 male and 50 Female,

Table 15: Ridge End Count summarized values 10 fingers

Finger Name	Male	Female
Left Thumb	13	16
Left Index Finger	1	16
Left Middle Finger	4	15
Left Ring Finger	14	21
Left Little Finger	13	15
Right Thumb	13	11
Right Index Finger	7	13
Right Middle Finger	13	17
Right Ring Finger	12	13
Right Little Finger	8	12

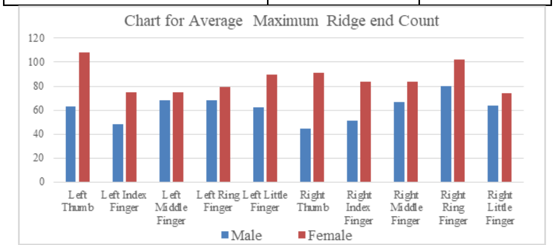


Female minimum ridge end counts are generally higher than male counts across all fingerprint categories, indicating a gender-specific pattern of more minimum ridge ends in female fingerprints. The minimum ridge end count for right hand thumb is greater than female count. Following Table 16 represents the summarized Ridge End Count values of the ten fingers of 50 male and 50 Female,

Table 16: Ridge End Count summarized values 10 fingers

Finger Name	Male	Female
Left Thumb	63	108
Left Index Finger	48	75
Left Middle Finger	68	75

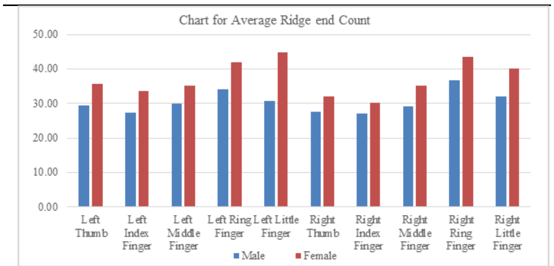
Left Ring Finger	68	79
Left Little Finger	62	90
Right Thumb	45	91
Right Index Finger	51	84
Right Middle Finger	67	84
Right Ring Finger	80	102
Right Little Finger	64	74



The average maximum ridge end count does not exhibit a consistent increasing or decreasing trend across fingers within each gender. There is variability in the patterns. Female maximum ridge end counts are generally higher than male counts across all fingerprint categories, indicating a gender-specific pattern of more maximum ridge ends in female fingerprints. Maximum ridge end count patterns between left and right hands are not consistently symmetrical, with some fingers showing higher counts on the left hand and others on the right hand. Similar to previous features, the Ring Finger consistently stands out with higher maximum ridge end counts compared to other fingers for both males and females, suggesting distinctive characteristics in this fingerprint category. Following Table 17 represents the summarized Ridge End Count values of the ten fingers,

Table 17: Ridge End Count summarized values of 10 fingers

Finger Name	Male	Female
Left Thumb	29.38	35.70
Left Index Finger	27.29	33.50
Left Middle Finger	29.90	35.17
Left Ring Finger	34.02	42.03
Left Little Finger	30.81	44.75
Right Thumb	27.58	31.97
Right Index Finger	26.98	30.11
Right Middle Finger	29.12	35.19
Right Ring Finger	36.63	43.44
Right Little Finger	32.10	40.06



The average ridge end count follows a general increasing trend from the Thumb to the Little Finger within each gender, suggesting a systematic variation in ridge end distribution. Female ridge end counts are consistently higher than male counts across all fingerprint categories, indicating a gender-specific pattern of more ridge ends in female fingerprints. There is a progressive increase in ridge end counts from the Thumb to the Little Finger for both genders, aligning with the expected anatomical variation in ridge patterns. Similar to previous features, the Ring Finger consistently stands out with higher ridge end counts compared to other fingers for both males and females, suggesting distinctive characteristics in this fingerprint category.

The analysis of various fingerprint features reveals distinctive patterns and variations. Across features such as ridge count, minutia count, bifurcation count, and ridge end count:

• Consistency and Variability: Some features exhibit consistent patterns across fingers (e.g., ridge end count), while others show variability (e.g., minutia count).

• Gender-Specific Patterns: Gender differences are noticeable, with females generally having higher counts in minutiae, bifurcations, and ridge ends.

• Finger-Specific Characteristics: Certain fingers, particularly the Ring Finger, consistently stand out with higher counts, suggesting unique characteristics.

• Biometric Relevance: The observed patterns have potential implications for biometric applications, emphasizing the need for gender-specific and finger-specific analysis.

• Progressive Trends: Progressive trends, such as the increase in ridge end counts from the Thumb to the Little Finger, align with expected anatomical variations.

6 Conclusion:

In conclusion, the detailed analysis of these fingerprint features provides valuable insights for biometric applications, forensic analysis, and the understanding of individual finger characteristics. The performance of the classification or identification algorithms are completely based on, type of features that we have selected, accuracy in extracted features, fingerprint features analysis before deciding the cluster structure, and finally the gender classification methods which can be designed with reference to the feature values analysis. In this paper the different types of feature extraction algorithms have studied. The paper has mainly focused on the analysis of the features before making the ranges of clusters as male and female for training mode. The research work is also in progress to design different classification algorithms for neural network and fuzzy c means algorithm.

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