

## Comparative Study of Selected Feature Extraction Techniques for Fingerprint Recognition

Aro Taye Oladele<sup>1</sup>, Tosho Uthman Adulrauf<sup>2</sup>, Oladejo Qazeem Ayokunle<sup>3</sup>, Issa Mariam Mohammed<sup>4</sup>, Ammarah Onyinoyi<sup>5</sup>, Yusuf Salma-Yusuf Omowunmi<sup>6</sup>, Ishaq Al-Ameen Muhammad<sup>7</sup>

<sup>1,2</sup> Department of Data Science and Technology, Alhikmah University, Ilorin, Nigeria

<sup>3,5,6,7</sup> Department of Computer Science, Alhikmah University, Ilorin, Kwara State, Nigeria

<sup>4</sup> Department of Computer Science, College of Arabic and Islamic Legal Studies, Nigeria

**ABSTRACT** In a fingerprint recognition system, feature extraction involves the actual process of transforming raw acquired fingerprint data images into a more useful representation for analysis or classification. The technique encompasses the identification and extraction of relevant characteristics from fingerprint image data. Feature extraction remains an effective method used to reduce the number of resources needed without losing vital information, and it has played a key role in improving the efficiency and accuracy of machine learning models or pattern recognition. This study conducted a comparative analysis of some selected feature extraction techniques for fingerprint recognition. Three feature extraction approaches, Discrete Wavelet Analysis (DWT), Minutiae, and Principal Component Analysis (PCA), were applied to extract features. The classification of extracted features was done using the Manhattan distance classifier. Evaluation of the developed fingerprint recognition system was achieved using two datasets: NIST DB4-Fingerprint Pattern and FVC2004 Dataset. The experimental results showed that the three selected feature extraction techniques and two fingerprint image datasets obtained results which revealed that the best accuracy value of 85.40%, was obtained in PCA, and the best FRR value of 9.80% was obtained in PCA, and best ERR value of 8.60% was recorded in PCA. Finally, it was shown that the performance of PCA was the best of the three feature extraction techniques for a fingerprint recognition system.

**KEYWORDS:** Feature extraction, fingerprint recognition, minutiae, principal component analysis, discrete wavelet transform.

### I. INTRODUCTION

Fingerprint recognition is one of the most widely used biometric authentication methods due to its reliability, uniqueness, and ease of use (Liébana-Cabanillas et al., 2024). Biometrics refers to the identification of individuals based on their physiological or behavioral traits, with fingerprints being one of the oldest and most studied biometric characteristics (Yu et al., 2023). The distinct patterns of ridges and valleys on a fingerprint make it a valuable tool for identity verification in various applications, including security systems, access control, and law enforcement. A fingerprint recognition system typically involves several steps, including image acquisition, preprocessing, feature extraction, and matching, with feature extraction playing a crucial role in determining the system's accuracy (Alqadi et al., 2021; Mohamed Abdul Cader et al., 2023). Feature extraction in fingerprint recognition involves identifying and representing key fingerprint characteristics in a form suitable for comparison (Socheat & Wang, 2020; Chen et al., 2025). Over the years, researchers have developed various feature extraction techniques to enhance the accuracy and efficiency of fingerprint recognition systems (Pradeep et al., 2025; Singh et al., 2025). Fingerprint recognition techniques can be broadly classified into structural, statistical, and spectral methods (Amrouni & Benzaoui, 2024;

Meiramkhanov & Tleubayeva, 2024). Among these, minutiae-based extraction, Principal Component Analysis (PCA), and Gabor filters are widely recognized for their effectiveness in fingerprint recognition (Narwal et al., 2016; Agarwal & Dixit, 2024). Among these, minutiae-based extraction, Principal Component Analysis (PCA), and Gabor filters are widely recognized for their effectiveness in fingerprint recognition (Tarawneh et al., 2022; Goyal et al., 2022). Each of these methods has unique strengths and weaknesses, making it essential to compare their performance under different conditions (Xiao et al., 2022).

The minutiae-based approach is the most commonly used technique in fingerprint recognition, as it mimics the manual fingerprint analysis performed by forensic experts (Garg, Singh, Singh, & Pratap, 2024). This method extracts specific ridge characteristics such as endings and bifurcations, which are then used for matching fingerprints. The reliability of minutiae-based systems has been widely shown, mostly for high-quality images (Alsharman et al., 2022). However, their performance can be affected by poor image quality, distortions, and partial fingerprints, making them less effective in certain scenarios (Chandana, Yadav, & Surendra, 2019; Socheat & Wang, 2020). PCA is a statistical technique used to reduce the dimensionality of fingerprint images while preserving important information (Weeraratne et al., 2024; Fadhil et al., 2024). By transforming high-dimensional data into a lower-dimensional representation, PCA helps in extracting essential features for fingerprint recognition. This method is particularly useful for improving computational efficiency and handling large datasets. However, PCA-based feature extraction may not capture fine details as effectively as minutiae-based techniques, especially in cases where fingerprints have complex patterns or distortions (Analysis & Projections, 2022; Wang & Chen, 2023). The discrete wavelet transform (DWT) is effective for fingerprint recognition due to its ability to obtain multi-resolution features, handle noise, and analyze texture, which improves accuracy, robustness, and classification performance (Meirista et al., 2024; Latif et al., 2024). It decomposes fingerprint images into multiple scales, allowing for simultaneous analysis of both frequency and spatial details. This multi-scale representation is particularly effective for capturing the intricate details and patterns (minutiae) essential for reliable identification. Many studies have compared the performance of different feature extraction techniques for fingerprint recognition. Some researchers have found that minutiae-based methods work best for high resolution images. Considering the aforementioned feature extraction techniques' robustness in fingerprint recognition system, there is a need to conduct a comparative analysis to show which of these techniques will perform well.

This paper conducted a comparative study on selected feature selection techniques: minutiae based, PCA-based, and DWT extraction techniques for fingerprint recognition. The evaluation in terms of accuracy, computational efficiency, and robustness against noise helps to identify the strengths and limitations of each method. The findings contribute to the development of more effective fingerprint recognition systems, which are essential for security, personal authentication, and forensic applications.

## II. RELATED WORKS

Chen et al., (2025) developed an approach that combined deep learning with feature descriptors for partial fingerprint matching. A Siamese Network was employed based on a CNN architecture for deep learning, complemented by a SIFT-based feature descriptor to obtain minimal yet significant features from the partial fingerprint. The final matching score was determined by integrating the outputs from both methods, using a weighted scheme. The experimental results, obtained from varying image sizes, sufficient epochs, and different datasets, showed that the combined approach gave an Equal Error Rate (EER) of approximately 4% for databases DB1 and DB3 in the FVC2002 dataset. Additionally, validation at FRR@FAR 1/50,000 yields result of about 6.36% and 8.11% for DB1 and DB2, respectively. Results showed the efficacy developed approach in partial fingerprint recognition.

Garg, Singh, Singh, and Singh (2024) proposed two techniques, inversion and multi augmentation, to augment the sample size with newly obtained images for each feature map. Multiple networks were used simultaneously for feature extraction from newly obtained images in parallel mode. Deep neural network

architectures were used with proposed inversion methods and multi-augmentation methods to classify the samples of fingerprints for personnel identification and verification. Pre-trained deep convolutional models like VGG16, VGG19, ResNet50, and InceptionV3 were fine-tuned with new processed fingerprint images for feature extraction and classification. The collective samples of fingerprints have been classified into 10 classes. The simulation results were obtained with diverse optimizers, and it was revealed that the VGG 19 model gave the accuracies of 88 % and 93 % with inversion and multi-augmentation techniques. Whereas, the VGG16 model recorded 93 % with the inversion approach and 97 % with the multi-augmentation technique. Thus, the proposed approach gave an accuracy of up to 97 % with the VGG16 model, which was significantly higher than that of any other model with the same dataset, FVC2000\_DB4.

(Mohamed Abdul Cader et al., 2023) surveyed fingerprint systems by analyzing the imaging techniques in fingerprint sensing that have been in existence for ten years. Nevertheless, the recent emerging trends and latest advancements in fingerprint sensing, image acquisition, and their problems have been left behind. Since the current reviews are either outdated or limited to a particular subset of the fingerprint systems, the study comprehensively analyzed the state of the art in the field of contact-based, contactless 2D and 3D fingerprint systems and their challenges in the facets of sensors, image acquisition, and interoperability. The open issues and challenges encountered in fingerprint systems, such as fingerprint performance, environmental factors, acceptability, and interoperability, and alternative directions are proposed for a better fingerprint system.

Ahmad, Farouk, Gambo, and Yusuf (2023) performed a comparative analysis of feature selection techniques for fingerprint recognition based on Artificial Bee Colony (ABC) and Teaching Learning Based Optimization (TLBO). The need to compare the performance of the two optimization techniques becomes necessary because the theoretical foundation of metaheuristic search algorithms suggests that no single algorithm is suitable for all problems. Hence, the better feature selection technique between the TLBO and ABC techniques in the fingerprint recognition system was investigated. Experimental results revealed that the TLBO technique outperformed the ABC technique and would produce a more reliable and accurate fingerprint authentication system. 3 (Alsharman et al., 2022) came up with a classification and matching fingerprint model, and the classification classifies fingerprints into three main categories (arch, loop, and whorl) based on a pattern mathematical model using GoogleNet, AlexNet, and ResNet Convolutional Neural Network (CNN) architecture and matching techniques based on bifurcation minutiae extraction. 'e model was implemented and tested using MATLAB based on the FVC2004 dataset. 'e obtained result revealed that the accuracy for classification was 100%, 75%, and 43.75% for GoogleNet, ResNet, and AlexNet, the time required to build a model was 262, 55, and 28 seconds for GoogleNet, ResNet, and AlexNet.

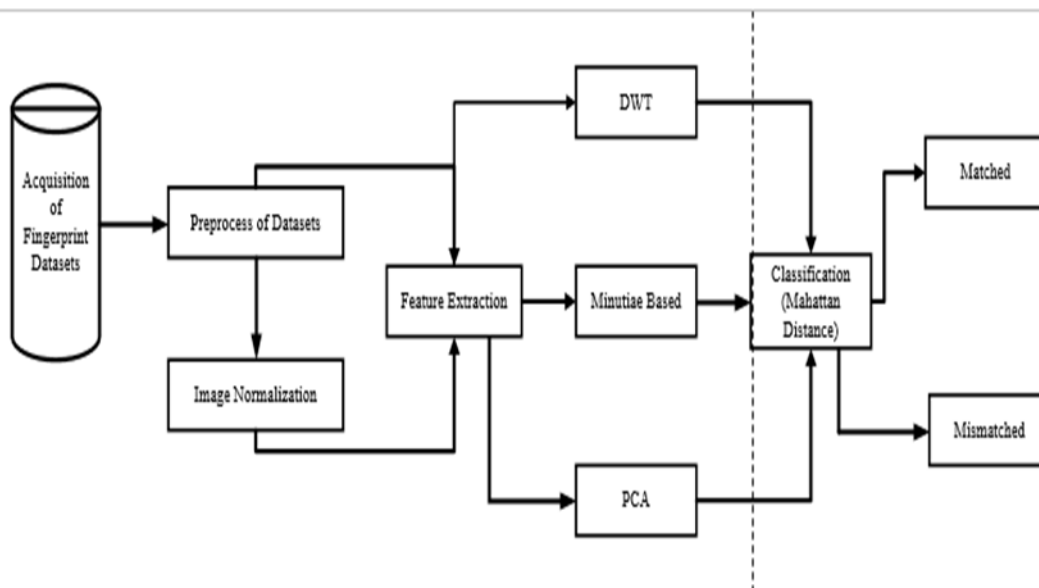
Alqadi, Abu-Faraj, Alqadi, and Aldebei (2021) analyzed the most famous methods used to extract fingerprint features. K-means, LBP, WPT, and minutiae methods were investigated; the obtained experimental results were analyzed and compared to raise suitable recommendations for using these methods. The process of extracting the fingerprint's characteristics is one of the important things for use in discrimination systems, which requires saving memory and accelerating the classification process to make the appropriate decision as quickly as possible. The stability of the properties of the fingerprint image, regardless of the different rotations, will lead to the use of a single feature vector for the fingerprint with its different conditions, and thus treat all the rotated fingerprints as one fingerprint image. This factor was studied in this study to recommend the experts interested in building fingerprint recognition systems. Patil and Nandusekar (2019) gave a comparison of thresholding algorithms (global thresholding and adaptive local thresholding), thinning algorithms, and a feature extraction algorithm to evaluate the best performance

of the algorithms in the fingerprint matching technique. Experimental results recorded the positive as well as negative sides of the different algorithms.

### III. METHODOLOGY

#### A. Comparative Study of Selected Feature Extraction for Fingerprint Recognition

The framework for this study serves as a structured approach to fingerprint recognition, outlining the step-by-step process from fingerprint acquisition to performance evaluation. It ensures a standardized workflow for comparing three feature extraction techniques: Minutiae-Based, PCA Based, and DWT methods. The framework includes key stages such as image acquisition, preprocessing, feature extraction, classification, and evaluation, as shown in Figure 3.1. During preprocessing, fingerprint images undergo noise reduction and contrast enhancement to improve clarity. The extracted features are then processed using different algorithms, and their performance is analyzed based on accuracy, processing speed, and robustness to distortions. This structured approach allows for a fair comparison of the techniques, ensuring consistency in evaluating their effectiveness.

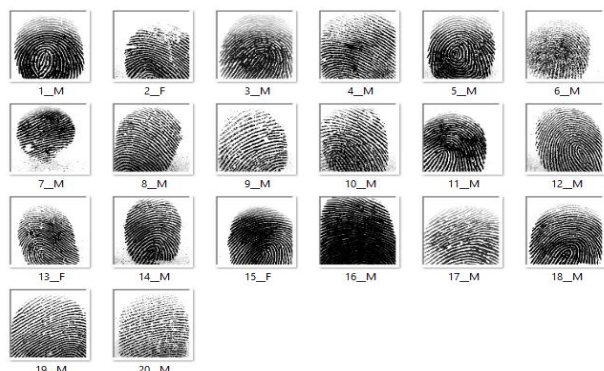


**Figure 1:** Proposed Model Architecture

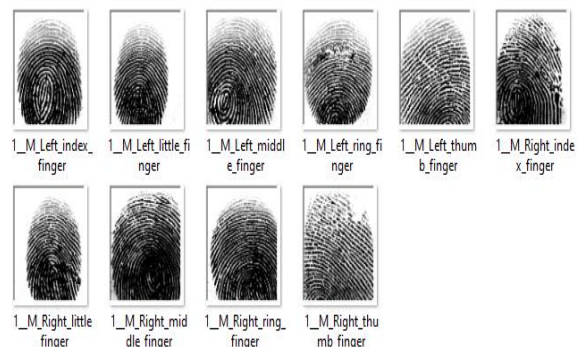
#### B. Acquisition of the Dataset

The fingerprint dataset used in this study is sourced from two commonly used biometric databases: the Fingerprint Verification Competition (FVC) datasets and the NIST Special Database 302. These datasets are widely recognized for their high-quality fingerprint images collected under varying conditions, ensuring diversity in terms of ridge patterns, orientations, and image quality. The FVC datasets provide benchmark fingerprint images from different competition years (e.g., FVC2000, FVC2002, FVC2004), containing impressions from multiple individuals with varying levels of distortion, noise, and sensor types. This ensures that the fingerprint recognition system is tested under realistic conditions. On the other hand, the NIST Special Database 302, developed by the National Institute of Standards and Technology (NIST), consists of high-resolution fingerprint images captured from diverse populations, supporting biometric research and algorithm evaluation. These datasets include different fingerprint classes. Arches, loops, and whorls allow a thorough assessment of the Minutiae-Based, PCA, and DWT feature extraction techniques. To ensure a fair evaluation, the dataset was divided into training and testing sets, where the training set was used to develop models and the testing set was used for performance evaluation. Selection criteria such as image clarity, resolution, and

number of impressions per individual are considered to maintain the reliability and effectiveness of the study. The samples of the two fingerprint datasets are shown in Figures 2 and 3



**Figure 2:** Sample of Fingerprint Database (FVC2004 Dataset)



**Figure 3:** Sample of Fingerprint Database (NIST DB4 -Fingerprint Pattern)

### C. Algorithm for Feature Extraction

Feature extraction is a crucial step in fingerprint recognition, as it involves identifying and processing key patterns in fingerprint images. In this study, three feature extraction techniques are implemented: Minutiae-Based Extraction, Principal Component Analysis (PCA), and Discrete Wavelet Transform Extraction. Each of these techniques extracts distinct fingerprint characteristics to improve the accuracy and reliability of biometric authentication.

#### (a) Algorithm for Minutiae-Based Feature Extraction

Minutiae-based feature extraction in fingerprints involves a series of steps to identify and extract unique features from fingerprint images, as discussed in Figure 4.

- Step 1: Start.
- Step 2: Acquire Image (Capture a clear fingerprint image).
- Step 3: Preprocess (Convert to grayscale, denoise, normalize, and segment the fingerprint area)
- Step 4: Enhance Ridges (Use Gabor or Fourier filters to highlight ridges).
- Step 5: Binarize (Convert image to black (ridges) and white (valleys))
- Step 6: Thin Image (Skeletonize ridges to 1-pixel width)
- Step 7: Detect Minutiae (Identify ridge endings and bifurcations using a 3×3 window)
- Step 8: Remove False Minutiae (Filter out spurious or closely spaced minutiae).
- Step 9: Format Features (Store each minutia as (x, y, angle, type).
- Step 10: Create Template (Compile minutiae data for matching or storage).
- Step 11: End

**Figure 4:** Algorithm of Minutiae-Based Feature Extraction

#### (b) Algorithm of PCA-based Feature Extraction

PCA is a dimensionality reduction method that is often used to reduce the dimensionality of large data sets by transforming a large set of variables into a smaller one that still contains most of the information in the large set, as shown in Figure 5.

Step 1: Start  
 Step 2: Standardize the range of continuous initial variables  
 Step 3: Compute the covariance matrix to identify correlations  
 Step 4: Compute the eigenvectors and eigenvalues of the covariance matrix to identify the principal components  
 Step 5: Create a feature vector to decide which principal components to keep  
 Step 6: Recast the data along the axes of the principal component  
 Step 7: End

**Figure 5:** Algorithm for PCA

### (c) Algorithm of Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform decomposes a signal into different frequency components by recursively applying low-pass and high-pass filters, followed by down sampling. The algorithm is given in Figure 6.

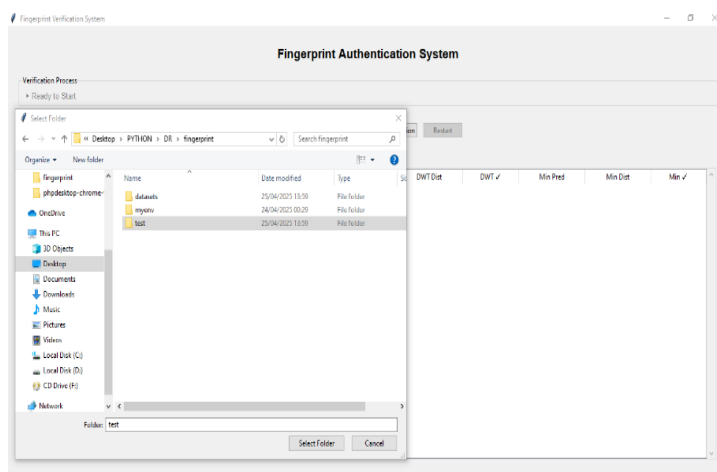
Step 1: Start  
 Step 2: Compute the DWT of a signal by passing it through a series of filters.  
 Step 3: Decompose SIGNAL simultaneously using a high-pass filter.  
 Step 4: If half the frequencies of the signal have been removed, half the samples can be discarded according to Nyquist's rule.  
 Step 5: End

**Figure 6:** Algorithm of DWT

## IV. Results and Discussion

### A. Loading of Fingerprint Database

Figure 7 shows the interface for loading of fingerprint authentication system.

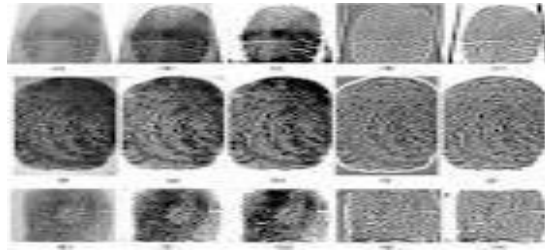


**Figure 7:** Interface for loading of fingerprint authentication system.



## B. Normalization of Fingerprint

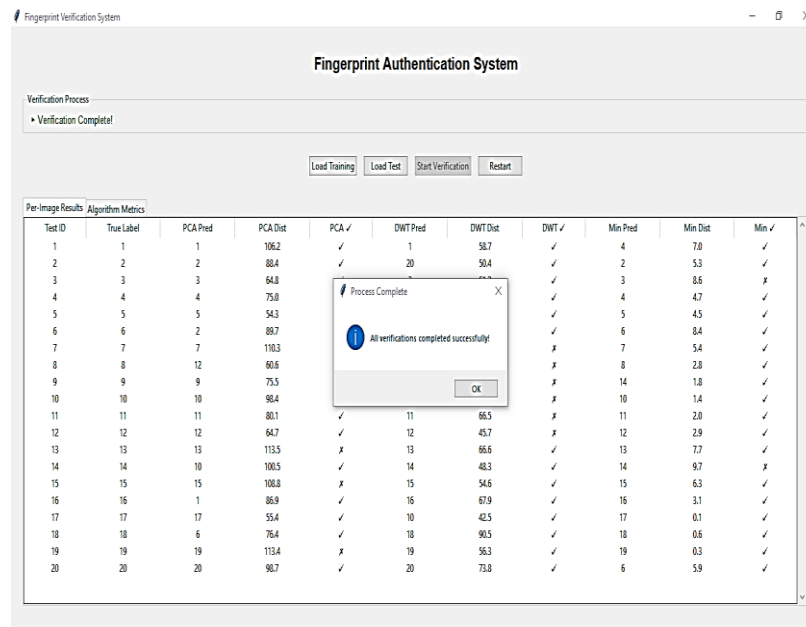
Fingerprint image normalization is a crucial pre-processing step in fingerprint recognition systems. It aims to improve image quality by adjusting pixel intensity values, removing noise, and enhancing contrast, particularly between ridges and valleys. This process, sometimes called contrast stretching, ensures a more uniform intensity distribution, making subsequent stages like enhancement, binarization, and minutiae extraction more reliable. This study applied histogram equalization techniques for normalization. The result of the fingerprint is shown in Figure 8.



**Figure 8:** Normalization of Fingerprint

## C. Training and Testing of Fingerprint Database

The interface of training and testing of the fingerprint dataset for fingerprint recognition is represented in Figure 9.



**Figure 9:** Training and Testing Phase

#### D. FEATURE EXTRACTION TECHNIQUES FOR FINGERPRINT

The results of the three-feature extraction techniques are represented in the following subsections

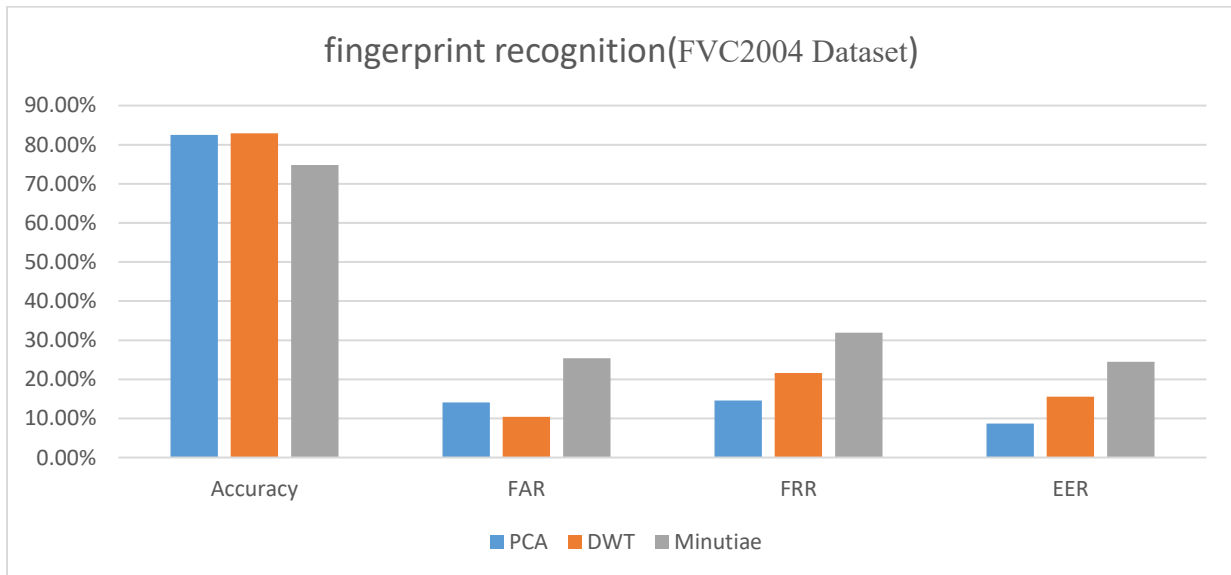
##### (a) Result of Feature Extraction (FVC2004 DATASET)

The result of feature extraction applying three selected feature extraction techniques is shown in Table 1 and Table 2. While the graphical representation is illustrated in Figure 10.

**Table 2:** Result of Fingerprint Feature Extraction (FVC2004 Dataset)

Algorithm	Accuracy	FAR	FRR	EER
PCA	82.50%	14.10%	14.60%	8.70%
DWT	82.90%	10.40%	21.60%	15.60%
Minutiae	74.80%	25.40%	31.90%	24.50%

In Table 2, analysis of the fingerprint recognition system gives the following results. The highest accuracy value of 82.90% was recorded in DWT. The highest FAR value of 25.40% was recorded in the minutiae-based feature extraction technique, the highest FRR value of 31.90% and the highest ERR value of 24.50% were obtained in the minutiae-based feature extraction technique.



**Figure 10:** Fingerprint Recognition System (FVC2004 Dataset)

##### (b) Result of Feature Extraction using Nist DB4-Fingerprint Pattern

The result of feature extraction applying three selected learning techniques using the NIST DB4-Fingerprint is shown in Table 3 and Table 4



**Table 1:** Result of Feature Extraction Techniques (FVC2004 Dataset)

TestID	TrueLabel	PCA_Pred	PCA_Dist	PCA_Correct	DWT_Pred	DWT_Dist	DWT_Correct	Min_Pred	Min_Dist	Min_Correct
1	1	1	99.10	Yes	1	42.4	Yes	17	3.6	Yes
2	2	2	90.40	Yes	1	98.9	No	1	3.9	Yes
3	3	3	68.0	Yes	3	67.1	Yes	3	1.7	Yes
4	4	20	56.5	Yes	6	58.1	Yes	4	9.6	No
5	5	16	52.80	No	5	50.1	Yes	5	5.9	No
6	6	3	78.10	Yes	6	59.9	Yes	6	6.4	Yes
7	7	13	80.65	Yes	17	40.6	Yes	7	8.8	No
8	8	8	110.4	Yes	8	86.8	Yes	8	0.2	Yes
9	9	9	92.9	Yes	9	49	Yes	9	4.6	No
10	10	1	105.4	Yes	10	55.1	Yes	10	2.2	No
11	11	11	59.5	No	11	67.5	No	11	1.9	Yes
12	12	10	1.1	Yes	12	72.9	Yes	12	7.4	Yes
13	13	13	115.7	Yes	13	64.5	No	13	8.4	Yes
14	14	14	69.7	Yes	14	81.9	Yes	7	2.3	No
15	15	15	89.3	Yes	15	87.7	Yes	16	5.9	Yes
16	16	16	86.9	Yes	16	69.6	Yes	16	6	Yes
17	17	17	93.4	Yes	17	72.4	Yes	17	9.3	No
18	18	18	92.7	Yes	18	79.5	Yes	18	9.1	Yes
19	19	19	77.2	Yes	17	66	Yes	19	2.5	Yes
20	20	20	73.1	Yes	20	94.9	No	20	9.4	Yes

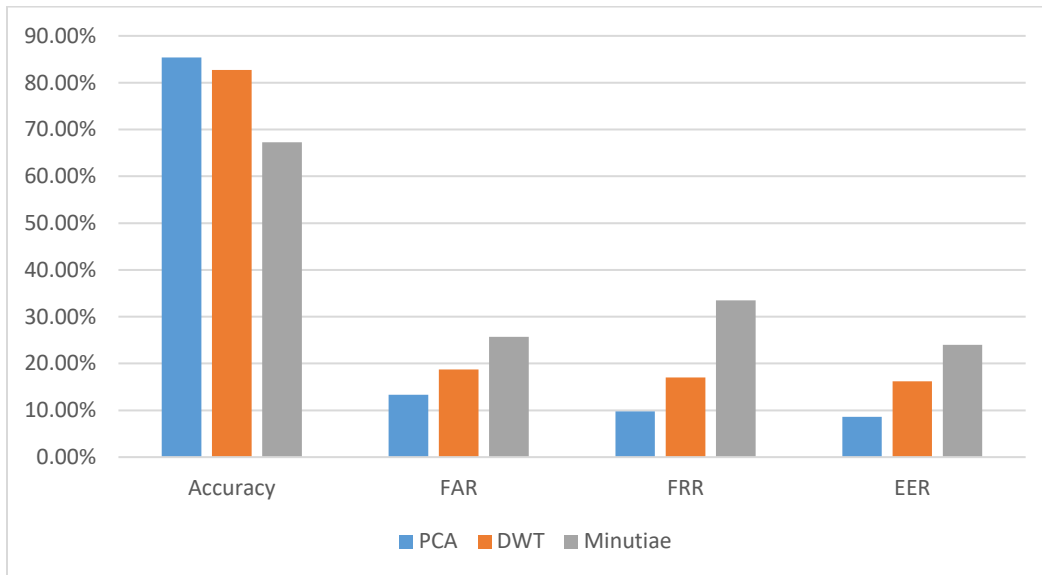
**Table 3:** Result of Feature Extraction for Fingerprint Recognition System (NIST DB4-Fingerprint Pattern)

TestID	TrueLabel	PCA_Pre_d	PCA_Dist	PCA_Correction	DWT_Pre_d	DWT_Dist	DWT_Correction	Min_Pre_d	Min_Dist	Min_Correction
1	1	1	53.8	Yes	1	92.8	Yes	1	7.4	Yes
2	2	3	82.1	Yes	2	41.9	Yes	2	8.9	Yes
3	3	3	117.9	Yes	3	64.8	Yes	3	6.9	No
4	4	4	67.7	Yes	13	46.2	Yes	7	0.9	Yes
5	5	5	97.2	Yes	5	54.9	Yes	5	3.2	No
6	6	6	50.3	Yes	17	55.1	Yes	15	3.9	Yes
7	7	7	97.4	Yes	7	41	Yes	11	0.2	Yes
8	8	8	89.1	Yes	8	69	Yes	6	4.5	No
9	9	9	70.7	Yes	9	72.6	Yes	9	4.9	No
10	10	10	105.6	Yes	10	45.9	Yes	10	9.3	Yes
11	11	11	62.2	No	11	84	No	11	10	Yes
12	12	12	72.4	Yes	12	95	Yes	12	8.1	Yes
13	13	13	83.2	Yes	13	68.2	Yes	13	1	Yes
14	14	15	59.3	Yes	14	64.1	Yes	14	2	No
15	15	15	110.5	Yes	15	58	Yes	13	7.9	Yes
16	16	16	61.6	Yes	16	45.8	Yes	16	8.6	No
17	17	17	72.9	Yes	10	83.6	Yes	17	9.3	No
18	18	18	112.2	Yes	18	44	Yes	18	3.5	No
19	19	19	111.8	Yes	19	59.1	Yes	19	9.4	No
20	20	3	97.5	Yes	20	56.7	No	20	8	Yes

**Table 4:** Fingerprint Recognition System (NIST DB4-Fingerprint Database)

Algorithm	Accuracy	FAR	FRR	EER
PCA	85.40%	13.30%	9.80%	8.60%
DWT	82.70%	18.70%	17.00%	16.20%
Minutiae	67.30%	25.70%	33.50%	24.00%

In Table 4, the analysis of the fingerprint recognition system gives the following results. The highest accuracy value of 85.40% in PCA. The highest FAR value of 25.70% was recorded in the minutiae-based feature extraction technique, the highest FRR value of 33.50% and the highest ERR value of 24.00% were obtained in the minutiae-based feature extraction approach for NIST DB4-Fingerprint Pattern.

**Figure 11:** Fingerprint Recognition System (NIST DB4-Fingerprint Database)

### (c) Comparative Study of Feature Extraction Techniques for Fingerprint Recognition

The section shows the comparative analysis of results of the fingerprint recognition system applying two fingerprint datasets: NIST DB4-Fingerprint Pattern and FVC2004 Dataset. The highest accuracy of 85.40% was obtained in PCA using NIST DB4-Fingerprint Pattern, the best FAR of 9.80% was recorded in PCA using NIST DB4-Fingerprint Pattern, the best FRR of 9.80% was recorded in PCA using NIST DB4-Fingerprint Pattern, and the best ERR of 8.60% was recorded in PCA using NIST DB4-Fingerprint Pattern. Finally, it was revealed that out of the two fingerprint image datasets and selected feature extraction techniques employed to evaluate the developed comparative study of feature extraction techniques for fingerprint recognition system, PCA with NIST DB4-Fingerprint Pattern outperformed other feature extraction techniques due to its ability to decrease the dimensionality of image data, leading to more efficient storage and computation, and its robustness to noise by filtering out insignificant variations.

## V. CONCLUSION

The feature extraction technique remains a significant phase of any fingerprint recognition model. Different feature-based feature extraction algorithms have been proposed by researchers in the field of pattern recognition (face, finger, or object recognition). The challenge is still on how to deduce the performance of individual feature extraction techniques in fingerprint recognition. The study adequately carried out an in-depth comparative analysis of the selected feature extraction approaches: Discrete Wavelet Transform (DWT), minutiae-based, and Principal Component Analysis (PCA) for fingerprint recognition systems. The output showed that PCA gave a robust result out of the three feature extraction techniques for fingerprint recognition systems. Further work should focus on the improvement of the feature extraction techniques via hybridization and also the enhancement of distance classifiers through the introduction of meta-algorithms.

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