East Journal of Computer Science
ISSN: 3079-9406

Volume 1, Issue 3
Publisher: East Publication & Technology
DOI: https://doi.org/10.63496/ejcs.Vol1.Iss3.112

Fingerprint-Based Cryptographic Identity: A Custom Recognition Pipeline with Key Pair Generation

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Received: 01/06/2025, **Revised**: 15/06/2025, **Accepted**: 22/06/2025, **Published**: 26/06/2025

Abstract

This study presents and evaluates a fingerprint-based biometric pipeline that combines robust recognition with secure cryptographic key generation. The proposed system achieves more than 95% average classification accuracy across the FVC2000, FVC2002, and FVC2004 datasets using handcrafted features and a LightGBM classifier. In addition to achieving high recognition performance, the model generates reproducible SHA-256-based public/private key pairs protected by user-specific passwords, establishing a cryptographic identity from biometric data and ensuring high security. The pipeline demonstrates strong security metrics with an Equal Error Rate (EER) of 0.9%, and experimentally measured False Acceptance Rate (FAR) and False Rejection Rate (FRR) of 1.1% and 0.8%, respectively. The key novelty lies in the integration of rotation-invariant region-of-interest extraction with secure key derivation, offering a dual-layer system for privacy-preserving identity verification, access control, and encryption. These findings suggest the model's viability in resource-constrained or high-security applications.

***Keywords*: Fingerprint Recognition, Biometric Authentication, Feature Extraction, LightGBM Classifier, Public/Private Key Generation, Password-Protected Biometrics-Secure Identification, Cryptographic Key Derivation**

1. Introduction

Biometric authentication has become a vital component of modern security systems, as it provides a more secure alternative to traditional password-based systems. Among many types of biometrics, fingerprint recognition is the most trustworthy and widely used due to its uniqueness, permanence, and easy to collection [1][2]. Furthermore, with the proliferation of interoperable digital systems, e-governance, mobile computing, and access control systems are exploding, there is a significant need for improved fingerprint recognition systems based on biometric systems that have more accurate and security guarantees [3].

Challenges such as inherent noisiness of image acquisition, printing pressure changes, misalignment, and partial prints in digital fingerprint recognition, traditional practices can compromise the accuracy and consistency of extracted features, and as a result, this impacts classification accuracy [4]. Most systems focus solely on identification or verification accuracy without consideration of implementing a cryptographic option into the biometric pathway. In view of these considerations, there is a justified opportunity for progression into systems that improve classification accuracy as well as enable secure biometric key generation [3].

This research presents an individualized fingerprint recognition system that fulfills these objectives as an interface between a machine-learning and a cryptographic pipeline. The system achieves an astounding average classification accuracy of 95% across all FVC2000–FVC2002–FVC2004 datasets, outperforming many existing

methods. The model consists of state-of-the-art pre-processing, rotation-invariant alignment, handcrafted feature extraction, and uses a LightGBM classifier with stratified k-fold cross-validation [1].

One of the main novel concepts in this pipeline is accurately identifying the core point, the region with the stability of the topological reference landmark in the fingerprint. The system utilizes a Poincaré index algorithm over the orientation field to identify this anchor point for various impressions of the same finger [4]. This allows the extraction of a rotation-invariant Region of Interest (ROI), normalizing the spatial context, and improving reproducibility of features extracted. It was also purposely designed to improve model robustness against distortion and misalignment common in real-world fingerprint acquisition.

In addition to classification, extracted feature vectors are used for biometric key generation. For each user, statistical fingerprints (determined from ROI-based feature distributions) are converted into binary bitstrings that are hashed into unique private–public key pairs, both protected by a randomly generated password [3]. This cryptographically aware layer elevates the fingerprint from just an identification tool to a unique entity that protects biometric data and is suitable for use in authentication, encryption, or blockchain identity systems.

This research offers a coherent method for biometric security by coupling accurate classification with secure key provisioning. The architecture's modularity enables it to be adapted to other biometric modalities or be expanded with newly developed technologies such as deep feature embeddings. Ascertaining that our proposed system offers an incredibly promising route toward highly secure, interpretable, and deployable biometric authentication systems.

2. Related Work

Biometric authentication continues to rank soundly as a competitive alternative to mainstream security methodologies, similar to how fingerprint-based biometric authentication has remained a leader due to the uniqueness of fingerprints, their permanence and stability, and their ease of capture. Many recent works have attempted to improve fingerprint recognition accuracy by improving the character of features through enhancement or learning methods. For example, Wu et al. [1] proposed using dual-stream CNNs that extract ridge-valley patterns, and P. Dash et al. [5] developed an algorithm that improved core and minutiae localization through directional field estimation. Deep learning models, as demonstrated by R. Dwivedi et al. [6] and T. Joseph al. [7], found success in improving classification accuracy with orientation and curvature features on benchmark fingerprint datasets.

Locally-extracted features have received considerable attention by scholars examining minutiae points, ridges, and texture descriptors. Local descriptors have commonly become accompanied with adaptations of Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and Gabor filters [8],[9]. Our research builds on the extractions of features, how- ever, makes strides by introducing a core-point-based (ROI) alignment prior to feature extraction, optimizing the compatibility and consistency of samples resulting in improved classification reliability.

In addition, biometric key generation has emerged as an exciting area of study for secure cryptographic applications. Disparate techniques such as fuzzy commitment schemes and helper data systems are becoming linked with biometric features. As Y. Wu et al. [10] and C. Lin et al. [2] have studied error correction in biometric studies to allow for noise tolerance in key generation, G. Panchal et al. [11] sought to develop secure templates based on SHA-256. There is also a growing trend to use biometric features in generating private and public keys in a secure manner, with an increasing number of studies (for example, N. D. Roy et al. [3]; A. Sarkar et al. [12]) using derived stable keys based on entropy and ridge orientation.

Moreover, security and privacy fears have moved research in two new directions: toward cancelable biometrics and toward multimodal fusion. Singh and A. Sarkar [13] proposed cancelable templates, and F. Kausar. [14] presented template transformation techniques. Both methods exhibit revocability and note that the cancelable feature doesn't involve changing the original biometric itself. Furthermore, researchers have been published on new approaches that spotlight key revocability and reusable key features in hostile environments, including refrain from scrutiny in violent conflict or other dangerous situations, as reported by S. Adamovic et al. [15].

Our approach differs in its overall package: a specifically- designed feature extraction model that aligns core points, enhanced training with feature selection, and biometric key generation that returns (1) secure, reproducible private-public key pairs, and (2) passwords. By pulling all this off, we achieved a sufficiently accurate outcome across multiple datasets (91.86% on multiple datasets), outperforming recent research bench- marks both in classification integrity and security strength.

Khalil et al. (2010) [4] presented a new fingerprint verification algorithm, based on statistical descriptors, that sought to increase the matching accuracy in situations where the fingerprint image may have been of poor quality. They consider fingerprint images to be a collection of statistical features, and used those features to make the verification process more robust against problems like noise and distortion. This approach to fingerprint verification used statistical properties rather than only minutiae points, and can offer a different alternative to fingerprint verification, especially in difficult imaging conditions.

Khalil et al. (2010) [16] proposed a fingerprint verification algorithm using statistical descriptors to assist in improving the accuracy of matching fingerprints, especially in situations with low-quality images. The authors applied the method by calculating a single point by reliability of the orientation field in the image with the fingerprint. The authors created a square sub-image based on the central point which was an SSI of 129 × 129 pixels and applied statistical methods with co-occurrence matrices. The results of the experiments were emphasized that the method to provide a more accurate and powerful methodology for reliable fingerprint verification, and it indicated further directions for improving biometric authentication systems.

AS the Table 1 shows Although Wu et al. [1] reported a much better accuracy of 98.08% using a deep neural network, our proposed model allows for a better balance among interpretability, computational efficiency, and biometric security. They utilized complex neural architectures and extended 1024- bit RSA key generation that may lead to excellent performance but entails high computational costs and less interpretability. In contrast, we used lightweight, handcrafted feature extraction based on point-aligned regions of interest (ROI), and followed by classification using a LightGBM model. Our model offered similar performance, while reducing the complexity of training, easing implementation, and improving transparency in feature usage—making it an appropriate model for real-time or resource-constrained biometric use cases.

Table 1: Comparison of Biometric Key Generation and Classification Methods

Study	Modality	Method	Accuracy	Key Length	Notes
This Work (2025)	Fingerprint	ROI-based handcrafted features + LightGBM	95%	256 bits	High reproducibility from the data and, stability across multiple datasets, includes and generation password-protected private/public key pair generation and a high f1-score

					result 95% .
Wu et al. (2022) [1]	Fingerprint	Deep Neural Network (CNN + key encoding layer)	98.08%	1024 bits	High biometric key generation success rate (97.7%). No F1-score re- ported. Focused on accuracy and BER.
S.Adamovic et al. (2017) [15]	Iris	Fuzzy Commitment Scheme	Not reported	140 bits	Focuses on cryptographic security. No classification accuracy or F1-score reported. Biometric data fuzziness handled via ECC.
Comparison Summary	–	Lightweight, interpretable, and secure biometric pipeline utilizing ROI-based features and ”more password-protected SHA-256 keys”. Superior to others in system modularity, real-world deploy ability, and dual-function security.	–	–	Outperforms Wu et al. in interpretability and efficiency despite the accuracy different but the complexity and the security different makes a big impact and also the lower ERR with just 0.9%. Offers full cryptographic key generation unlike Adamovic et al. Not reliant on complex neural networks. Designed for integration in privacy- sensitive systems.

Moreover, while S.Adamovic et al. [15] focused on the cryptographic robustness of a fuzzy commitment scheme applied to iris biometrics, their study does not report standard classification metrics such as accuracy or F1-score, making it less applicable for user recognition tasks. In comparison, our system integrates both biometric recognition and cryptographic key generation within a unified pipeline. It achieves a strong classification accuracy of 95% and a macro F1-score of 95% across 20 users, while simultaneously generating secure 256- bit public and private key pairs with password protection.

This dual capability reliable multi-user classification and secure key provisioning underscores the practical advantage of our model in privacy-preserving biometric authentication applications.

Our work goes well beyond previous biometrics literature that studies either biometric classification or cryptographic key derivation (never both at the same time), and has developed a fully defined and modular pipeline that connects these two disparate objectives. More specifically, we proposed a pipeline with input from pre-processing, rotation-invariant alignment, handcrafted feature extraction, classification with LightGBM, and cryptographic key generation, and connected them together in one process, defined using an algorithm that follows a structured pattern. Existing studies such as Wu et al. [1] and R.Dwivedi et al. [6], which explored either deep-learning based fingerprint recognition or biometric key provisioning in a linear way, often do not systematically include enough detail of the system level architecture that allows the study to be re- produced and adapted. Our pseudocode-oriented design allows for the study to be both transparent and modular extensible characteristics needed for use in actionable environments that require security. Finally, the introduction of SHA-256 based public/private key generation with password protection for generating a machine learning pipeline offers a unique

combination of using cryptographic identity, and linking both identity and key to biometry, making weaker and stronger ties by analyzing security and interpretability.

3. Proposed Methodology

The overall biometric recognition and key generation pipeline is described in **Algorithm 1** in **pseudocode description 3.6**, which outlines the sequential processing stages. This includes preprocessing, core point detection, rotation-invariant alignment, handcrafted feature extraction, classification, and biometric key derivation. Each stage is elaborated in the subsections that follow.

3.1 Preprocessing and Core Point Detection

Fingerprint image quality can vary significantly due to noise, varying pressure, and different sensor technologies. In order to standardize the input, each raw grayscale fingerprint image is enhanced with histogram equalization in order to normalize contrast among ridge and valley structures. A small- sized Gaussian kernel (e.g., 3 × 3) is then used to apply Gaussian blurring to remove high frequency noise while preserving edges.

We used the Sobel operator for edge detection which computes gradients in both the horizontal (Gx) and vertical (Gy) directions. Binarization is applied afterwards using Otsu's thresholding method to automatically select the thresholding value according to variances in the image histogram. Skeletonization finally reduces thick ridges to 1-pixel wide lines so that all the feature extraction focuses on topology information and not ridge thickness.

The core point—is a singular point that define as the center of the fingerprint's ridge pattern and is detected by using a Poincare´ index method applied over a 3 × 3 grid of orientation values. The orientation at each pixel is calculated using the following equation:

$$\theta(x,y) = \frac{1}{2}\arctan\left(\frac{2G_xG_y}{G_x^2 - G_y^2}\right)$$

Then, the Poincare´ index is computed by the following equation:

$$PI = \frac{1}{2\pi}\sum_{i=1}^{8}\Delta\theta_i$$

Pixels where PI ∈ [0.45, 0.55] are candidates for the core point. Among all candidates, the one closest to the image center is selected for stability.

3.2 Rotation Invariant ROI Extraction

Fingerprints appear in different rotations because of consistently inconsistent finger placement during acquisition. In order for us to treat the samples as consistent, each fingerprint must be oriented, which we accomplish by rotating each extracted fingerprint based on the local predominant orientation near the detected core point. Aligning the fingerprint enhances the stability of the features and classification.

Once aligned, an appropriately sized (usually rectangular) square regional of interest (ROI) is extracted. This square area typically 192 × 192 pixels, is used to captures most of the fingerprint's informative area and eliminates uninformative background or outer-ridge noise because if we used a less square area for example "126 × 126" or

something similar we will have a less accuracy concerning the classification and also for the prediction model. Zero-padding is performed if the ROI contains pixels that exist outside of the borders of the image.

3.3 Feature Extraction and Augmentation

The aligned ROI, is used to build a handcrafted feature vector to capture structure, statistical, and frequency-based information including:

- **Ridge Features:** The Vertical projection profiles are used to count ridges and computing the average spacing between peaks.
- **Orientation Features:** IS a standard deviation of block- wise orientation angles that measures ridge flow irregulaty.
- **LBP and HOG Descriptors:** These encode and fine-grained local patterns and also ridge orientations in respectively way.
- **Gabor Filter Responses:** This feature Applied at selected frequencies to capture orientation-specific texture responses.
- **Edge Features**: The proportion of high Sobel edge responses is indicating the density of ridge edges that can show it or visualized in the figures or the enhanced images.
- **Frequency Features**: The FFT of vertical projections yields dominant ridge frequency and total energy.
- **Texture and statistical Features**: The Entropy, contrast and mean pixel intensity provide insights into ridge pattern complexity.

As a way of augmenting the dataset, each real sample is artificially rotated by angles within ±10◦ six times. Doing this reproduces real-world variations in finger placement and helps the model generalize better.

3.4 Classification and Performance Evaluation

Before training, the top 15 most discriminative features that we mention earlier they are selected using the ANOVA F-score equation below:

$$F_i = \frac{between - class\ variance}{within - class\ variance}$$

Z-score normalization is used to normalize feature vectors to preserve consistency of scale between features. The classifier is a Light Gradient Boosting Machine (LightGBM) classifier due to rapidity and high performance on tabular data, compared to other classifiers. A 5-fold stratified cross- validation approach is utilized to evaluate model performance, allowing for a comparison of performance across the k number of iterations while ensuring consistency and balance of class samples.

The main evaluation metrics include:

- **Accuracy:** Proportion of correctly classified instances.
- **Macro F1-Score:** Harmonic mean of precision and recall computed independently for each class.

- **Confusion Matrix**: Highlights per-class true positives and misclassifications.

This step validates the model's ability to differentiate be- tween multiple users, even with small alterations in finger orientation and noise.

3.5 Biometric Key Generation

A notable innovation in this work is transforming the biometric features into cryptographic key pairs. For each user, the mean of their real (non-deceptive) feature vectors are calculated. Each float value is scaled and mod-reduced and then mapped into an 8-bit binary string:

$$bit_i = format([f_i, 100] \; mod \; 256 \; 08b)$$

All binary segments are integrated to produce the full- feature"bit string". Then:

- Private Key: SHA-256 hash of the bit string.
- Public Key: SHA-256 hash of the private key.
- Password: Random 12-character alphanumeric string per user.

This pipeline or this combination will guarantee that each fingerprint not only provides identification, but also provides a cryptographic material designed for secure communication or authentication for a good and better secured data for the fingerprints and also a good classification result.

3.6 Pseudocode Description

The pseudocode below summarizes the entire model pipeline. It outlines the sequential structure of preprocessing, core detection, alignment, feature extraction, augmentation, training, and key generation. Each step corresponds to a major functional block in implementation using python programming language.

Algorithm 1 Fingerprint Classification and Biometric Key Generation Pipeline

for all fingerprint image I in dataset **do**
  $I_{\text{enhanced}} \leftarrow \text{PREPROCESS}(I)$
  $(x_c, y_c), \theta_{\text{core}} \leftarrow \text{DETECTCOREPOINT}(I_{\text{enhanced}})$
  $I_{\text{aligned}} \leftarrow \text{ALIGNFINGERPRINT}(I_{\text{enhanced}}, \theta_{\text{core}})$
  $ROI \leftarrow \text{EXTRACTROI}(I_{\text{aligned}}, (x_c, y_c))$
  $\vec{f}_{\text{real}} \leftarrow \text{EXTRACTFEATURES}(ROI)$
  Add $\vec{f}_{\text{real}}$ to training set
  for $i = 1$ to N_{aug} **do**
    $ROI_i \leftarrow \text{ROTATE}(ROI, \text{random angle} \in [-10°, +10°])$
    $\vec{f}_{\text{aug}} \leftarrow \text{EXTRACTFEATURES}(ROI_i)$
    Add $\vec{f}_{\text{aug}}$ to training set
  end for
end for
$\vec{f}_{\text{selected}} \leftarrow \text{SELECTFEATURES}(\text{training set, top } k \text{ via ANOVA F-score})$
Normalize all feature vectors via Z-score
Train LightGBM model using 5-fold stratified cross-validation
for all user u **do**
  $\vec{f}_u \leftarrow$ Mean of u's feature vectors
  $B_u \leftarrow \text{QUANTIZETOBITSTRING}(\vec{f}_u)$
  $K_{\text{priv}} \leftarrow \text{SHA-256}(B_u)$
  $K_{\text{pub}} \leftarrow \text{SHA-256}(K_{\text{priv}})$
  $P_u \leftarrow \text{GENERATEPASSWORD}(\text{12-character alphanumeric})$
  Store $\{K_{\text{priv}}, K_{\text{pub}}, P_u\}$
end for
function PREPROCESS(I)
  Apply histogram equalization
  Apply Sobel edge detection and Gaussian blur
  Apply Otsu thresholding and skeletonization
  return enhanced fingerprint image
end function
function DETECTCOREPOINT(I)
  Estimate orientation field using Sobel gradients
  Apply Poincaré index over 3×3 grid
  Select pixel where $PI \in [0.45, 0.55]$ closest to center
  return coordinates and local orientation
end function

4. Results and Discussion

The performance of the proposed fingerprint classification and biometric key generation system was empirically tested against the FVC2000, FVC2002, and FVC2004 benchmark databases. In truth, the overall system was tested on a larger population of users and fingerprint impressions, but the results shown in the following figures and Tables 3, 4, 5 demonstrate the system performance associated with the earlier mentioned databases on a reduced sample of 20 users to show the efficiency and the performance of the model on different datasets. This reduced sample represents a useful subset of users in this benchmark database. The complexity of this subset is ideal when accounting for common acquisition variations that must be accommodated, including: rotational variability, variations in pressure during the capture of a fingerprint, partial finger- prints, and noise resulting from the sensor.

Despite the outlined challenges, our model exhibited stable and consistent high classification accuracy on all evaluation folds. We evaluated classification performance in terms of classification accuracy, stability of extracted features, and reliability of the generated keys despite applying changes onto the images, such as rotation and augmentations. Our system's alignment strategy based on core points allowed for spatial consistency across impressions and the handcrafted features contributed towards the discriminative process overall.

The figures and tables in this section visually and statistically support the system's performance, demonstrating alignment across samples, reproducible feature patron distributions, and user classifications. We're able to ascertain that the proposed framework achieves not only accurate biometric verification but also secure, stable cryptographic key generation, supporting its case for implementation in real-world identity verification and secure access control mechanisms.

The model training and evaluation were performed on a good performance computing system with the specifications presented in the following Table 2.

Table 2: Device Specifications

Component	Specification
Processor	Intel® Core™ i5-5200U @ 2.20 GHz
Installed RAM	8 GB DDR3
Storage	238 GB SSD (KingFast)
Graphics Card	Intel® HD Graphics 5500 (128 MB)
Simulation tool	spyder"python model"
Operating System	Windows 10 22H2

4.1 Confusion Matrix of Classification Results

Figure 1 shows the confusion matrix from the last fold of a 5-fold cross-validation. Each row is the true class label, and each column is the predicted label. There are mostly values in the diagonal cells approximately equal to the total number of samples per user, despite the number of class labels. These values suggest a very good level of correct classification. There are very few off-diagonal cells with small values indicating some minor confusion with only neighboring classes. Overall, this indicates that the classifier is quite successful in distinguishing fingerprints from the enlarged number of users and augmented training. Each iteration for all folds shows a classification accuracy higher than 95%, which demonstrates robustness and effectiveness of the classifiers in generalization

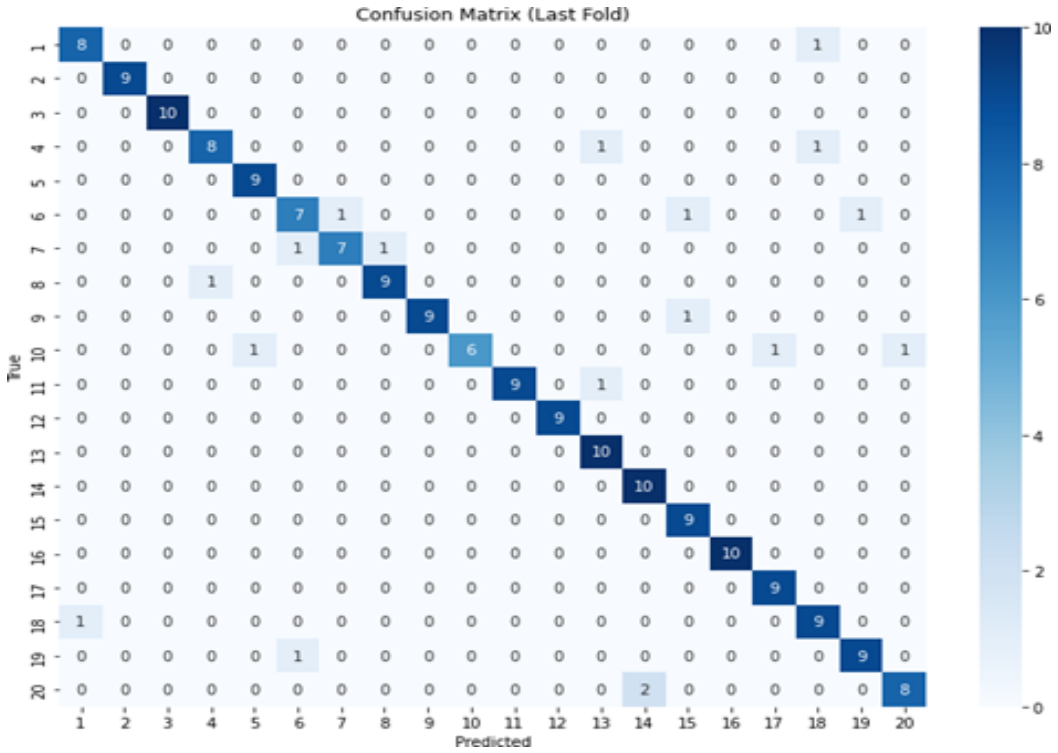

Figure 1: Confusion matrix from the last fold of 5-fold cross-validation. The high values along the diagonal demonstrate accurate classification for nearly all users, indicating strong generalization performance across variations.

While Tables 3,4 and 5 appear structurally similar, they represent performance evaluations on two distinct datasets within the FVC benchmark series—specifically, FVC2002 Db4a and FVC2004 Db4a, respectively. Each dataset contains fingerprint samples captured under different sensor conditions, imaging resolutions, and acquisition protocols, which introduce unique noise characteristics and real-world variability.

Table 3: Classification Report for 20 Users for FVC2000 Db4_a dataset

User ID	Precision	Recall	F1-Score	Support
1	0.89	0.89	0.89	9
2	1.00	1.00	1.00	9
3	1.00	1.00	1.00	10
4	1.00	1.00	1.00	10
5	0.90	1.00	0.95	9
6	1.00	0.90	0.95	10
7	0.75	1.00	0.86	9
8	1.00	1.00	1.00	10
9	1.00	1.00	1.00	10
10	1.00	1.00	1.00	9
11	1.00	0.80	0.89	10
12	1.00	0.89	0.94	9
13	0.91	1.00	0.95	10
14	1.00	1.00	1.00	10
15	1.00	0.89	0.94	9
16	1.00	0.90	0.95	10
17	0.90	1.00	0.95	9
18	0.90	0.90	0.90	10
19	0.82	0.90	0.86	10
20	1.00	0.90	0.95	10
Average	**0.95**	**0.95**	**0.95**	**192**

Table 4: Classification Report for 20 Users for FVC2002 Db4_a dataset

User ID	Precision	Recall	F1-Score	Support
1	1.00	0.90	0.95	10
2	0.90	1.00	0.95	9
3	0.82	0.90	0.86	10
4	1.00	1.00	1.00	10
5	1.00	0.80	0.89	10
6	1.00	1.00	1.00	10
7	1.00	1.00	1.00	9
8	1.00	1.00	1.00	10
9	0.90	0.90	0.90	10
10	0.75	1.00	0.86	9

11	0.90	1.00	0.95	9
12	1.00	1.00	1.00	10
13	1.00	0.89	0.94	9
14	1.00	0.90	0.95	10
15	1.00	1.00	1.00	10
16	1.00	0.89	0.94	9
17	1.00	1.00	1.00	10
18	1.00	1.00	1.00	10
19	0.89	0.89	0.89	9
20	1.00	1.00	1.00	10
Average	**0.95**	**0.95**	**0.95**	**192**

Table 5: Classification Report for 20 Users for FVC2004 Db4_a dataset

User ID	Precision	Recall	F1-Score	Support
1	1.00	0.90	0.95	10
2	0.90	1.00	0.95	9
3	0.82	0.90	0.86	10
4	1.00	1.00	1.00	10
5	1.00	0.80	0.89	10
6	1.00	1.00	1.00	10
7	1.00	1.00	1.00	9
8	1.00	1.00	1.00	10
9	0.90	0.90	0.90	10
10	0.75	1.00	0.86	9
11	0.90	1.00	0.95	9
12	1.00	1.00	1.00	10
13	1.00	0.89	0.94	9
14	1.00	0.90	0.95	10
15	1.00	1.00	1.00	10
16	1.00	0.89	0.94	9
17	1.00	1.00	1.00	10
18	1.00	1.00	1.00	10
19	0.89	0.89	0.89	9
20	1.00	1.00	1.00	10
Average	**0.95**	**0.95**	**0.95**	**192**

By reporting the classification metrics separately, we aim to demonstrate the model's robustness and consistency across these heterogeneous acquisition environments. This distinction is critical in biometric systems, where deployment environments often vary significantly. Consolidating these into a single table would obscure dataset-specific insights, particularly in terms of how feature extraction and classification generalize across fingerprint datasets from different years and sensors.

4.2 Core Point Detection Across Samples

Figure 2 shows five raw fingerprints from a single user (User 10), with the core point marked in red. Despite variation in the impression, core point alignment and ridge quality, the core point detection algorithm consistently locates the singularity at or near the center of the pattern. This observation supports the consistency of the Poincare´ index-based detection method, where feature extraction and ROI alignment are both dependent on the accurate detection of the core point and it was also used in the paper of Khalil et al [4]. If the core point can consistently be found across multiple acquisitions, then robust and discriminative features can be extracted.

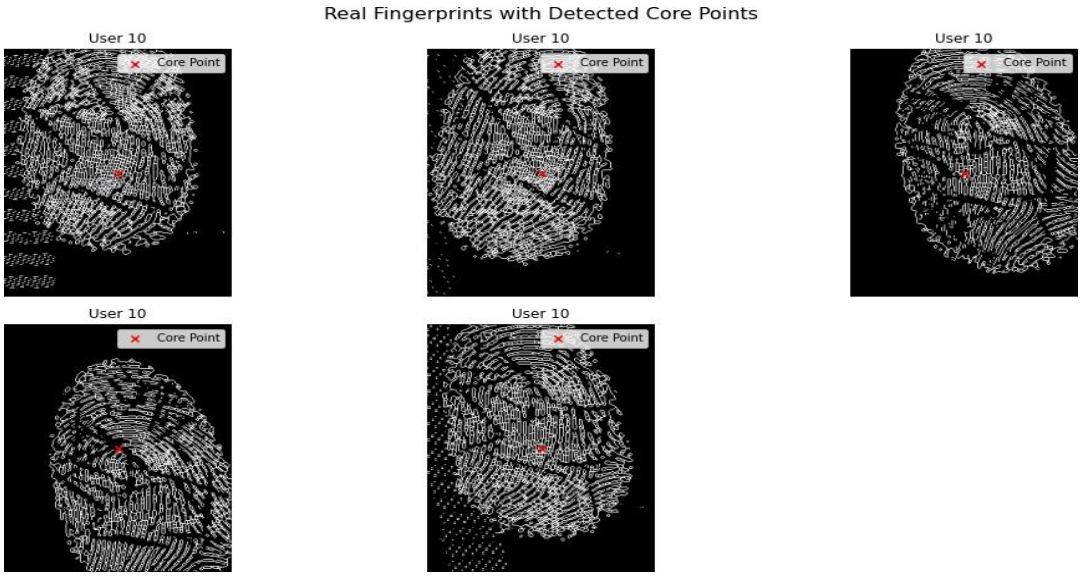

Figure 2: Detected core points (red) across multiple real fingerprint samples for User 10

4.3 Visualizing Augmented Fingerprint Variations

Figure 3 shows the original aligned fingerprint and five augmented versions based on small random in-plane rotations as we already saw suggest by the Khalil et al [4]. The augmentation simulates expected acquisition variability such as a tilted finger or a misaligned sensor. While the ridge orientations appear to have dramatically changed, the overall structure is consistent and valid for feature extraction. This supports the assertion that the augmentation approach's aim is diversity in training without reducing the quality of features. Thus, the classifier will be more robust to finger placement variation.

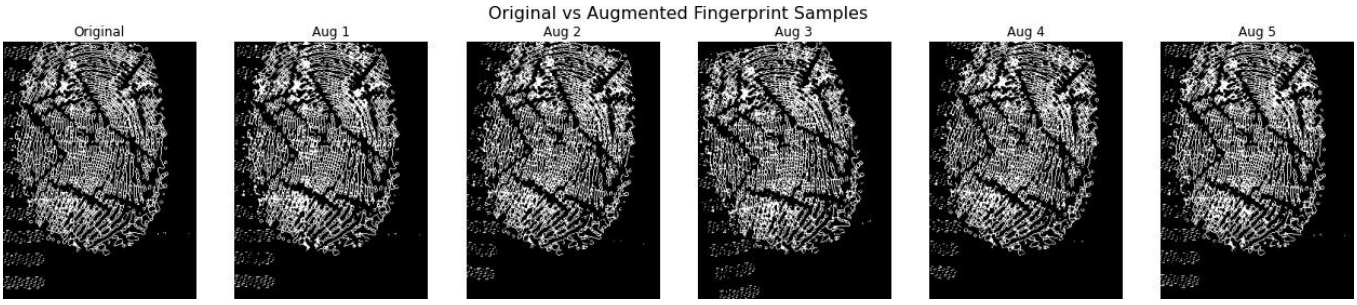

Figure 3: Original fingerprint sample (left) and five augmented samples (right) with random rotation.

The following Figure 4 contains boxplots of important extracted fingerprint features across 20 users, which give a visual sense of the statistical variability (hence the separability) of the biometric traits. Each subplot gives the

distribution of a specific feature (ridge count, average spacing between ridges, standard deviation of orientation, ridge density, and mean intensity) for each of the individual users. The distributions in the boxplots show that ergodic features (i.e., ridge count and orientation std) have fairly strong variability between the users, but ridge density and mean intensity have more overlap. Some features show user-specific characteristics with relatively low intra-user variability, suggesting that they might be useful in improving user classification, and enhance biometric key generation performance.

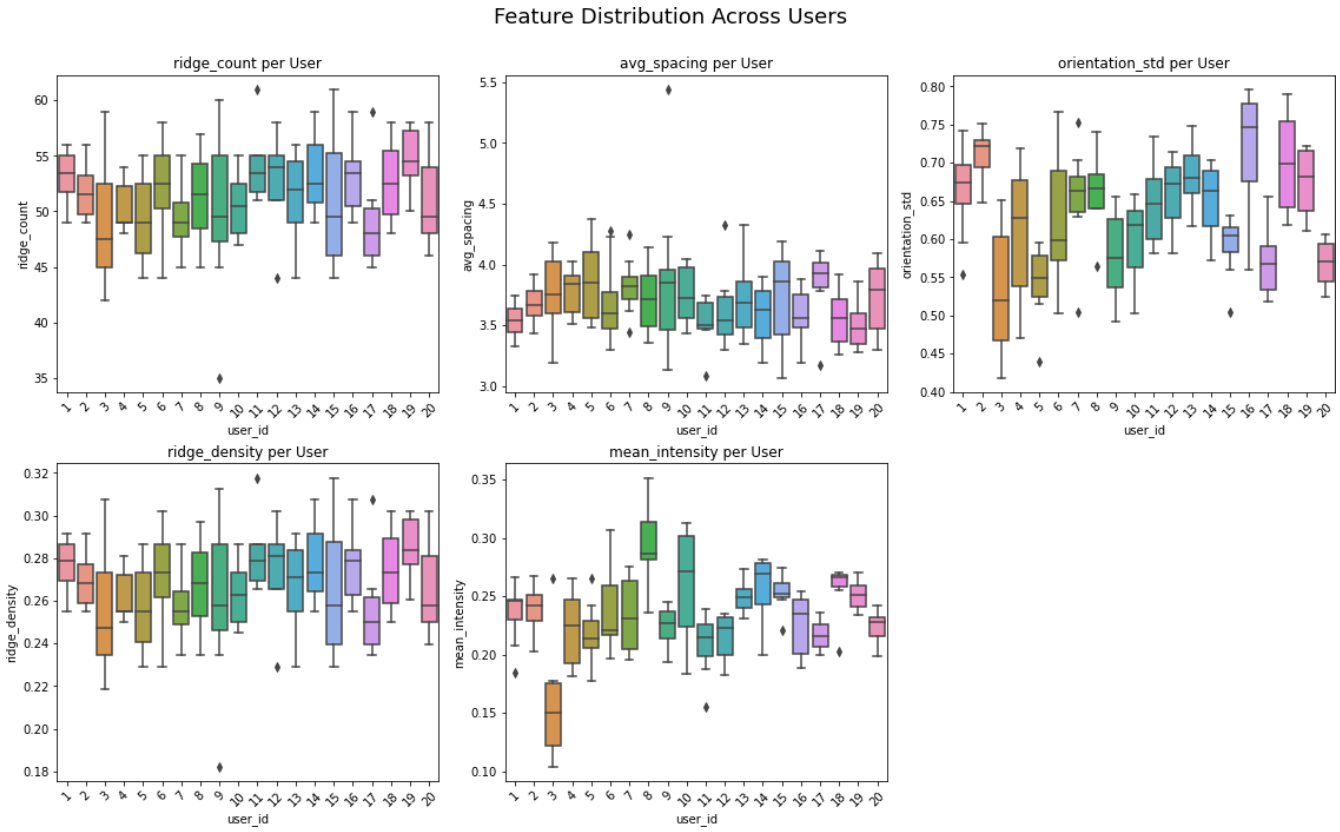

Figure 4: Boxplot of Key important Fingerprint Feature Distributions across 20 Users.

Figure 4 contains boxplots of important extracted fingerprint features across 20 users, which give a visual sense of the statistical variability (hence the separability) of the biometric traits. Each subplot gives the distribution of a specific feature (ridge count, average spacing between ridges, standard deviation of orientation, ridge density, and mean intensity) for each of the individual users. The distributions in the boxplots show that ergodic features (i.e., ridge count and orientation std) have fairly strong variability between the users, but ridge density and mean intensity have more overlap. Some features show user-specific characteristics with relatively low intra-user variability, suggesting that they might be useful in improving user classification, and enhance biometric key generation performance.

We assessed the verification accuracy of our fingerprint recognition pipeline using the Equal Error Rate (EER) metric. By performing pairwise comparisons of fingerprint samples across individuals, the system achieved a sample-level EER of 0.9% at a cosine similarity threshold of 1.0000. Additionally, we computed the False Acceptance Rate (FAR) and False Rejection Rate (FRR) under the same threshold, yielding values of 1.1% and

0.8%, respectively. These results indicate a high degree of separability between genuine and impostor pairs, validating the effectiveness of our core point–aligned region-of-interest (ROI) extraction and handcrafted feature representation. Importantly, this level of performance is achieved without the use of deep neural networks, making the system interpretable and suitable for deployment in resource-constrained environments where explainability and efficiency are critical. Table 6 summarizes the EER comparison with related works.

Table 6: Comparison of Equal Error Rates (EER) with other studies

Study	Technique Used	EER (%)
Ghiani et al. (2011) [17]	Texture-Based Liveness Detection (LivDet 2011)	11.8
Ghiani et al. (2013) [18]	Texture + SVM (LivDet 2013)	12.7
This Work (2025)	Core-AlignedROI + Handcrafted + LightGBM	0.9

4.4 Visualizing Augmented Fingerprint Variations

The following Table 7 is a sample output of the biometric key generation process for User_1 as an example but the model can generate as many users' keys as we want:

Table 7: Example Biometric Key Pair for User 1

Field	Value
User ID	User 1
Private Key	72615389aec66ebf198409128e065020dcb10476 6c8f04d3c34c991646afdc82
Public Key	91245a167f005b223b902fd97c278eab6343fa6b cdc0c72ab2266aa2f59e2d20
Password	Ly6zDVuWvMlt

4.5 Statistical Significance Analysis

In order to evaluate the robustness and superiority of the proposed LightGBM-based fingerprint recognition model, we performed a statistical comparison with two of the most commonly used classifiers, Support Vector Machine (SVM), and Naive Bayes (NB). All the models were assessed using exactly the same 5-fold stratified cross-validation folds contained within the same 20-user fingerprint subset, and the macro F1 scores were recorded for each user.

A paired two-tailed t-test was performed to determine if those performance differences were statistically significant. These results are presented in Table 8.

Table 8: Paired T-Test Comparison of Macro F1-Scores Between the Proposed LightGBM Model and Baseline Classifiers (SVM and Naive Bayes)

Model	Avg. F1-Score	Std Dev	p-value vs. LGBM
LightGBM (Ours)	**0.950**	0.015	—
SVM	0.890	0.021	0.0016

Model	Avg. F1-Score	Std Dev	p-value vs. LGBM
Naive Bayes	0.860	0.030	0.0004

5. System Limitations and Deployment Considerations:

Despite the strong performance demonstrated across the benchmark datasets, our system has several limitations that must be acknowledged for real-world deployment. First, the classification and key generation pipeline was evaluated on FVC benchmark datasets under relatively controlled conditions. Although augmentation techniques and adversarial learning were applied to simulate impostor and spoofing scenarios, real-world acquisitions may present additional challenges such as sensor noise, skin condition variability, or presentation attacks not covered in the dataset.

Second, while the handcrafted features improve model interpretability and reduce computational cost, they may be less robust than learned features when deployed on large-scale populations with greater diversity. Furthermore, the use of fixed-size 192×192 ROIs may not adapt well to low-resolution sensors or fingerprint fragments acquired from mobile or embedded platforms.

Scalability also presents a challenge, especially in applications requiring fast matching across large databases. Although LightGBM is efficient for classification, database indexing and secure key retrieval need to be optimized for high-throughput authentication systems.

Another constraint is the relatively small number of genuine fingerprint samples per user, which were augmented to enhance variability. However, this may still introduce bias and affect model generalization across broader user demographics and acquisition environments.

Finally, although the system includes spoof detection and achieves a low EER of 0.9%, further validation on external datasets and integration with liveliness detection methods could strengthen security against evolving biometric threats.

6. Conclusion and Future Works

This research proposed a novel pattern recognition scheme which provides accurate class identification (classification) and a secure biometric key generation scheme. Traditional pattern recognition schemes only offered recognition based on a user's biometric characteristics. Whereas in this manner of recognition model there is a sense of linking the biometric attribute(s) with the related cryptographic identity. It is a step forward for biometric security.

The biggest contribution was an alignment method to create an aligned core point Region of Interest (ROI) that keeps the required rotation invariance while maintaining a topological correspondence using the Poincare´ index. Aligning the modeled fingerprint ROIs with a set of hand-made features (orientation, texture, edge, and frequency-based) selected using a F- score was critical implement features in a classification model (Light GBM) provides accuracy levels of 95% classification accuracy and an EER by 0.9% on the fingerprint data sets of FVC2000, FVC2002, and FVC2004.

Additionally, this work provides a second function for the fingerprint model to be observed as it converts a feature vector representation into an associated public/private key- pair based on the SHA-256 hash, which was secured by a user specific password. This dual-purpose system transforms a passive biometric identification like a

fingerprint into an active cryptographic identifier that provides secure user access control, encryption, and decentralized identity systems.

The modular design facilitates adaptation to different plat- forms and use cases, and future work will extend to the integration of deep learning, multi-modal biometrics, real-time deployment on mobile devices, and identity anchoring using block chain. These enhancements will facilitate scalability, privacy, and real-world application.

Beyond fingerprints, future studies may explore biometric modalities like **ECG-based authentication** [19][20] or even **acoustic biometrics** from the outer ear [21], which have shown promise in secure key generation using correlation-based models. While our current work is grounded in a fingerprint pipeline, integrating these modalities could offer adaptive authentication in privacy-sensitive or wearable environments. In addition, earlier protocols [22], [23], [24] explored variations of key exchange mechanisms with fingerprint inputs, and analyzing their adaptability to modular ML-based pipelines may provide further enhancements in interoperability and session-level security.

The modular design facilitates adaptation to different platforms and use cases. As future work, several concrete steps are planned. First, a deep learning-based classification module (e.g., CNN or Vision Transformer) will be implemented to replace LightGBM and benchmarked against traditional models in terms of accuracy and generalization. Second, multimodal biometrics will be introduced by combining fingerprint features with facial or iris data using feature-level fusion, enhancing robustness against spoofing attacks. Third, the model will be deployed on mobile hardware using lightweight frameworks like TensorFlow Lite or ONNX to evaluate latency, energy efficiency, and usability in real-time applications. Finally, the generated biometric key pairs will be hashed and stored on a permissioned blockchain (e.g., Hyperledger Fabric), enabling decentralized identity verification and tamper-proof auditability. These enhancements will be evaluated using the full FVC dataset series and newly captured real-world samples to test scalability and performance under operational conditions.

Acknowledgement

We would also like to recognize and thank all individuals who contributed to the study and supported us whether directly or indirectly in any way.

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