ENHANCING EXAMINATION INTEGRITY THROUGH FINGERPRINT RECOGNITION SYSTEM

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Abstract

This study investigates a fingerprint recognition system utilizing Pseudo Zernike Moments (PZMs) to enhance examination integrity by mitigating impersonation risks. The performance of the PZMs method was rigorously compared to traditional Minutiae-based and Pattern-based techniques, focusing on key metrics such as recognition accuracy and processing time. The PZMs method achieved a recognition accuracy of 91.81 %, significantly higher than 88 % for Minutiae-based and 85 % for Pattern-based methods ($p < 0.05$), with processing times of 1011 ms, compared to 1200 ms for Minutiae-based and 900 ms for Pattern-based methods. The overall recognition rate was 98.67%, with a minimal False Rejection Rate (FRR) of 0% and a Failure to Enroll Rate (FER) of 1.33%. These results demonstrate that the PZMs-based system significantly enhances exam security by effectively reducing the risk of impersonation. The study also addresses critical challenges related to scalability and privacy concerns associated with biometric data. Future research directions include exploring the integration of PZMs with other biometric modalities and neural networks to further enhance system performance and applicability beyond academic settings.

Keywords: fingerprint recognition; examination integrity; *Pseudo Zernike Moments*; biometrics; impersonation prevention

Introduction

Fingerprint biometrics, which uses the unique patterns of an individual's fingerprints for identification or verification, is one of the most reliable and widely adopted biometric methods. Each person's fingerprints are distinct and remain unchanged throughout their life, making them ideal for secure identification (Smith *et al.*, 2019). Due to their accuracy and ease of use, fingerprint recognition systems have been successfully deployed in various sectors, including law enforcement, banking, and personal device security (Lee and Kim, 2021).

A fingerprint consists of several unique features, such as ridges, valleys, and minutiae points (small details like ridge endings and bifurcations). These features are extracted and analysed by fingerprint recognition systems to create a unique digital "fingerprint template" for each individual (Garcia and Martinez, 2020). This template is then compared to stored templates for identity verification. Since no two people share the same fingerprint pattern, fingerprint biometrics are highly reliable for security purposes (Wilson and Brown, 2021).

Fingerprint biometrics can significantly improve the security of examinations in both academic and professional settings. Examinations are essential for evaluating a person's knowledge and skills critically (Eguavoen and Nwelih, 2023), but their integrity is often compromised by impersonation, where one person takes an exam on behalf of another. This undermines the fairness of the exam process and diminishes the value of earned qualifications (Brown and Johnson, 2020). Traditional identity verification methods, such as photo IDs and signatures are increasingly insufficient to prevent impersonation and fraud. These methods are prone to forgery, manipulation, and human error, making them unreliable for securing high-stakes exams (Johnson and White, 2020).

As the number of exam candidates grows and the need for fast, accurate identity verification increases, the limitations of traditional methods become more apparent. Manual checks are time-consuming and often fail to detect impersonation, which threatens the fairness and security of the exam process (Smith *et al*., 2019). In contrast, fingerprint biometrics provide a much more secure and reliable solution. By using the unique patterns of fingerprints, these systems can effectively prevent fraud, ensuring that only the rightful candidate can take the exam.

Fingerprint recognition systems offer a robust solution by verifying a candidate’s identity through their unique fingerprint patterns, making it nearly impossible for an impersonator to bypass the system (Gupta and Singh, 2020). Unlike traditional methods, fingerprint biometrics are difficult to forge or duplicate, and these systems are fast and easy to use. They are particularly suited for large-scale examination environments where many candidates need to be verified in a short period (Clark and Harris, 2021).

In addition to enhancing security, fingerprint recognition systems offer convenience. Candidates simply place their finger on a scanner for verification, eliminating the need for physical identification documents that can be lost or forgotten. Moreover, advancements in fingerprint recognition technology have improved accuracy, even when dealing with distorted or incomplete fingerprints (Williams and Davis, 2021).

This research investigates the use of fingerprint biometrics to enhance examination security by preventing impersonation. By analyzing the benefits of fingerprint recognition and its application in exam environments, the study aims to demonstrate how this technology can safeguard exam integrity and provide a reliable, secure solution for identity verification in high-stakes testing scenarios (Jones *et al*., 2021).

Problem Statement

Fingerprint recognition systems are widely regarded for their reliability; however, traditional methods such as minutiae-based and pattern-based techniques reveal significant limitations, particularly in modern examination environments. These methods often struggle with issues related to noise, distortion, and the presence of partial prints. Such deficiencies become critical in fast-paced settings where quick and accurate identification is paramount (Smith *et al*., 2019). As a result, these conventional techniques prove insufficient for ensuring the high levels of accuracy and speed required to maintain fairness and security during assessments.

In contrast, Pseudo Zernike Moments (PZMs) offer a more effective solution to these challenges. PZMs excel at capturing the global characteristics of fingerprint images, making them more resilient to noise and distortion. Additionally, they are capable of handling partial prints, significantly enhancing recognition accuracy. By leveraging the advantages of PZMs, this study seeks to explore advanced fingerprint recognition techniques that not only address the shortcomings of traditional methods but also improve processing speed and accuracy in examination settings. Ultimately, this approach aims to bolster the integrity of assessment processes and provide a reliable means of preventing impersonation in critical evaluation environments.

Objectives of the Study

The primary objective of this study is to develop and evaluate a fingerprint recognition system using Pseudo Zernike Moments (PZMs) to enhance examination integrity by preventing impersonation. The specific objectives are:

i. To collect and pre-process fingerprint data using wavelength transformation techniques.
ii. To analyze fingerprint images using PZMs for feature extraction.
iii. To implement the fingerprint recognition system using Python 3.9 and implemented on Microsoft Visual Studio 2022.
iv. To evaluate the system's recognition accuracy and processing time.
v. To compare the performance of the PZMs method with traditional fingerprint recognition methods.

Biometric Authentication

Biometric authentication systems have become increasingly essential in enhancing security by utilizing unique physiological or behavioural traits, such as fingerprints, facial recognition, iris patterns, and voice recognition, to verify individual identities. These systems offer a more secure alternative to traditional methods like passwords or ID cards, as biometric characteristics are inherently unique and difficult to replicate (Jones *et al*., 2020). However, the growing reliance on biometric systems has spurred ongoing research into their limitations and potential areas for improvement, particularly in terms of accuracy, privacy, and cost-effectiveness (Jain *et al*., 2023).

Biometric authentication systems typically consist of three main stages: enrolment, storage, and verification/identification. During enrolment, biometric data is captured and processed to extract distinctive features, which are stored in a secure database. In the verification stage, the system compares a newly captured biometric sample with the stored template to confirm an individual's identity, while the identification process involves searching the database for a match (Maltoni *et al*., 2021). Recent research, however, highlights ongoing challenges such as potential data breaches, spoofing attacks and privacy concerns related to the sensitive nature of biometric data (Ratha *et al*., 2022). Addressing these issues has become a focal point in recent studies, with several proposing solutions such as decentralized biometric databases and advanced liveness detection methods (Jain *et al*., 2022).

Fingerprint Recognition

Among the various biometric modalities, fingerprint recognition remains one of the most widely adopted due to its reliability, ease of use, and the distinctive, unchanging nature of fingerprint patterns (Maltoni *et al*., 2021). Fingerprint recognition systems operate in several stages: image acquisition, pre-processing, feature extraction, and matching. Image acquisition involves capturing a high-resolution image of the fingerprint, followed by pre-processing to remove noise. In the feature extraction stage, key points, such as minutiae and ridge endings, are identified. Finally, these features are compared with stored templates to confirm the individual's identity (Jain *et al*., 2023).

While fingerprint recognition has proven to be an effective biometric solution, recent research emphasizes the need to address its limitations, particularly in dealing with poor-quality images, distortions, and varying environmental conditions (Zhang *et al*., 2022). Studies within the past five years have focused on improving recognition accuracy through advanced machine learning and deep learning algorithms that automatically enhance feature extraction and matching (Li *et al*., 2022). However, challenges such as spoofing attacks and ensuring the system's accuracy across diverse populations and conditions persist, creating gaps in the literature that this research seeks to address.

Techniques for Fingerprint Recognition

Traditional fingerprint recognition techniques are primarily divided into two categories: minutiae-based and pattern-based approaches. Minutiae-based methods focus on identifying specific fingerprint features like ridge endings and bifurcations, offering high accuracy but requiring high-resolution images to perform effectively (Zhang *et al*., 2021). On the other hand, pattern-based techniques analyze the overall ridge flow and texture of the fingerprint, making them less sensitive to image quality but generally offering lower accuracy compared to minutiae-based methods (Li *et al*., 2021).

Recent advancements have introduced new techniques that address the limitations of traditional methods, particularly in large-scale, real-world applications. One such method is Pseudo Zernike Moments (PZMs), which provide a mathematical representation of fingerprint images using orthogonal polynomials. This approach captures intricate details and patterns, offering advantages like rotational invariance and robustness to noise, which are crucial for handling degraded or noisy fingerprint images often encountered in large-scale environments, such as exam halls or airports (Ma *et al*., 2020). PZMs' ability to maintain high recognition accuracy under challenging conditions distinguishes them from other techniques like minutiae-based or pattern-based methods, which can struggle with distorted or low-quality images (Chen *et al*., 2023).

However, a critical gap in the literature is the lack of research on computational efficiency of PZMs in large-scale applications, such as examination security systems, where thousands of fingerprints need to be processed in real-time. While PZMs are known for their robustness, their real-world applicability in terms of processing speed and scalability remains underexplored. Addressing this gap is a key objective of this research, which aims to assess the trade-offs between accuracy and computational efficiency in large-scale biometric systems.

Moreover, recent studies have increasingly integrated machine learning and deep learning techniques into fingerprint recognition systems to enhance accuracy and reliability (Chen *et al.*, 2022). Convolutional Neural Networks (CNNs), for instance, have shown promising results by automatically learning the most relevant fingerprint features from large datasets, reducing the reliance on manual feature extraction. However, the literature lacks a critical analysis of how these models perform under varying real-world conditions, such as in noisy or low-quality fingerprint scenarios, which this study aims to investigate.

Applications in Examination Security

The use of biometric authentication, particularly fingerprint recognition, in examination security has garnered increasing attention in recent years as educational institutions face rising incidents of impersonation and academic dishonesty. Traditional methods like ID cards and manual identity verification are proving insufficient in preventing such activities, prompting the need for more secure and reliable systems (Jones *et al.*, 2022). Fingerprint recognition offers an effective solution by ensuring that only the registered candidate is allowed to take the exam, thereby enhancing the credibility and integrity of the examination process (Li *et al.*, 2022).

Fingerprint systems can be seamlessly integrated into the examination process. During the registration phase, students' fingerprints are captured and securely stored in a database. On exam day, students authenticate their identities by scanning their fingerprints, which are then compared against the stored templates (Chen *et al.*, 2021). This ensures a streamlined and non-intrusive verification process that can significantly reduce the risk of impersonation.

Despite these advantages, challenges remain, particularly regarding the scalability and speed of fingerprint recognition systems in large-scale exam environments. With thousands of students needing to be authenticated simultaneously, the system's ability to process data efficiently while maintaining high accuracy is critical. Current literature lacks in-depth studies that address this specific issue, representing a key gap that this research aims to fill by exploring more computationally efficient algorithms, such as PZMs, for real-time examination security systems (Jain *et al.*, 2023).

Moreover, concerns about privacy and data security must be addressed. As fingerprint data is sensitive and immutable, ensuring that biometric information is securely stored and protected from unauthorized access or breaches is paramount. While the literature acknowledges these concerns, further exploration is needed into the development of privacy-preserving biometric systems, such as those using decentralized databases and advanced encryption techniques (Ratha *et al.*, 2022). This research will explore these solutions and evaluate their feasibility in the context of examination security systems.

Methodology

Architectural design of the system

The architectural design of the minutiae-based fingerprint recognition system is depicted in Figure 1. This architecture encompasses various modules, each with a specific function that collectively ensures the accurate recognition of fingerprints for the purpose of preventing impersonation during examinations.

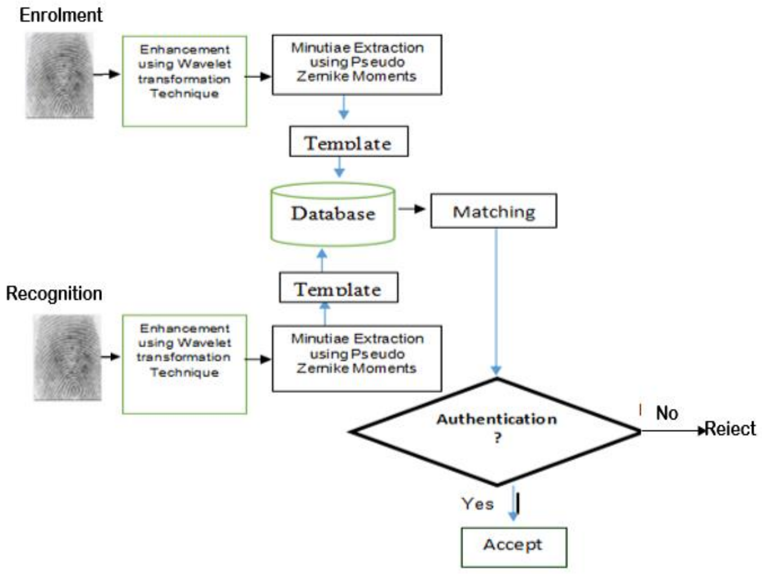

Enrolment
Enhancement using Wavelet transformation Technique
Minutiae Extraction using Pseudo Zemike Moments
Template
Database
Matching
Recognition
Template
Enhancement using Wavelet transformation Technique
Minutiae Extraction using Pseudo Zemike Moments
Authentication ?
No
Reject
Yes
Accept

Figure 1: Architectural diagram of the system

Components of the System Architecture

The system architecture for fingerprint recognition is designed to ensure accurate and efficient biometric authentication by combining image acquisition, pre-processing, feature extraction, and matching processes. This section provides an overview of each component, offering a clearer understanding of how the system functions without diving too deeply into mathematical details, which are now addressed in the appendix for clarity and readability.

Enrolment Module:

This module initiates the system by capturing high-quality fingerprint images using a suitable sensor or reader. The focus here is on extracting the **minutiae points**, distinctive features like ridge endings and bifurcations from the fingerprint. Ensuring image quality at this stage is crucial, as it directly impacts the accuracy of later processes such as feature extraction. The system's performance depends on the precision of data captured during this phase.

Database Module:

The database stores preprocessed fingerprint images that have undergone enhancement techniques to ensure consistency and high quality. These images serve as the foundation for the system's fingerprint recognition algorithms, providing reliable data for authentication and verification. A well-organized and comprehensive database enhances both the system's accuracy and its capacity to handle large datasets, which is essential for real-time identification tasks, especially in large-scale applications like exam security.

Enhancement Module:

This module focuses on improving the quality of the raw fingerprint images before feature extraction. The enhancement process uses **wavelet transformation** to break down the image into multiple layers of detail, improving contrast and edge sharpness. The transformation effectively emphasizes fingerprint features that might otherwise be lost in noisy or low-quality images.

Wavelet Transformation Parameters: The wavelet transformation's parameters, such as the level of decomposition and choice of wavelet function, are carefully selected to maximize feature clarity while minimizing the impact of noise. These parameters are tuned based on the quality of the initial fingerprint images. In this system, a mid-level decomposition has been chosen to balance the trade-off between image detail and computational efficiency.

Normalization Process: After applying wavelet transformation, the fingerprint images are normalized. This involves adjusting pixel intensity values to fit within a standard range, which helps mitigate variations caused by environmental factors like lighting or pressure during image capture. By standardizing these images, the system ensures more consistent performance across different conditions.

This pre-processing step significantly improves the system's ability to extract discriminatory features from the fingerprint, leading to better recognition accuracy. Details on the specific parameters and their tuning are provided in the appendix.

Extraction Module:

After the images are enhanced, the system extracts unique fingerprint features using **Pseudo Zernike Moments (PZMs)**. PZMs provide a robust method for representing the fingerprint image, capturing intricate details in a way that is less sensitive to noise compared to traditional methods. They offer several advantages over conventional techniques, including:

Noise Robustness: PZMs produce longer feature vectors, making them more resistant to image quality issues like noise or distortions. This is particularly useful in real-world applications where fingerprint images may not always be captured under ideal conditions.

***Higher Feature Representation Capacity*:** PZMs generate feature vectors with more dimensions (e.g., 66 for PZMs compared to 36 for Zernike Moments), leading to improved accuracy in matching. This makes them well-suited for large-scale systems, such as exam security environments, where computational efficiency and precision are critical.

The system computes the distance between **ridge endings** and **bifurcations**—the minutiae points—by measuring the **Euclidean distance** between them. This forms the basis for fingerprint matching during the verification process. The detailed mathematical formulations for PZMs and the Euclidean distance calculation have been moved to the appendix for ease of reading.

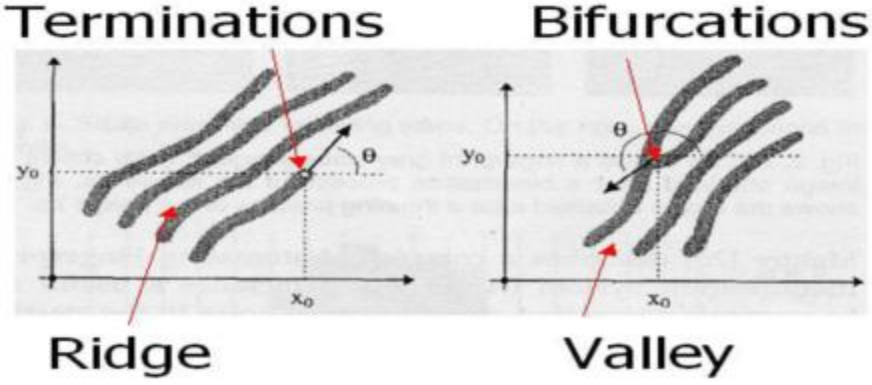


Figure 2: Minutiae ending and bifurcation

Figure 2 illustrates the two key types of minutiae points: ridge endings and bifurcations. Ridge endings occur where a fingerprint ridge terminates, while bifurcations represent where a ridge splits into two. These minutiae points for the foundation for fingerprint feature extraction and matching processes.

Data Collection

Data were collected from 150 individuals using a digital personal biometric sensor. This device captured high-resolution images of fingerprints, which were then enhanced using wavelet transformation techniques. The minutiae were extracted from the fingerprints using the *Pseudo Zernike Moments* algorithm. Table 3.1 illustrates sample data used in this research, showing the Euclidean distance calculations between ridge endings and bifurcations.

Table 1: Euclidean distance of sample data collected

User	**Minutiae Measurement**		**(q_i-p_i)**	**(q_i-p_i)^2**	$\mathbf{d = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2}}$
	p_i	q_i			
Fpint 1	7	9	2	4	2
Fpint 2	5	8	3	9	3
Fpint 3	9	10	1	1	1
Fpint 4	2	4	2	4	2
Fpint 5	9	10	1	1	1
Fpint 6	8	11	3	9	3
“	“	“	“	“	“
Fpint 150	2	4	2	4	2

Table 1 shows the Euclidean distance of sample data collected by calculating the distance between the ridge ending and bifurcation. The measurement is between the *termination* which is the immediate ending of a ridge and the *bifurcation* which is the point on the ridges where two branches are bifurcated.

Storage System and Matching Module:

The storage system acts as a repository for the fingerprint templates, securely storing them in a database. The matching module is responsible for comparing scores from a claimed identity with the stored templates. The degree of similarity, ranging from 0 (total mismatch) to 1 (perfect match), enables the system to make accurate decisions about the user’s identity.

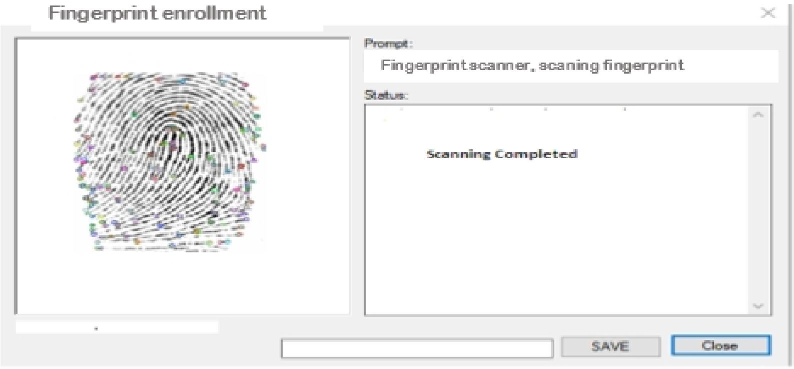
System Implementation:

The prototype for the fingerprint recognition system was developed using Python 3.9 and implemented on Microsoft Visual Studio 2022. The system was run on a MacBook Pro with a 2.6 GHz Intel Core i7 CPU, 16 GB RAM, and a 1TB SSD. The system's interface includes components for fingerprint enrolment, verification, and storage of images and templates.

Result and Discussion

The fingerprint image extraction and enrolment process

The minutia feature of fingerprint images is extracted using Pseudo Zernike Moment and the model is discussed in section above, while the fingerprint enrolment process is depicted in Figure 3.



Fingerprint enrollment

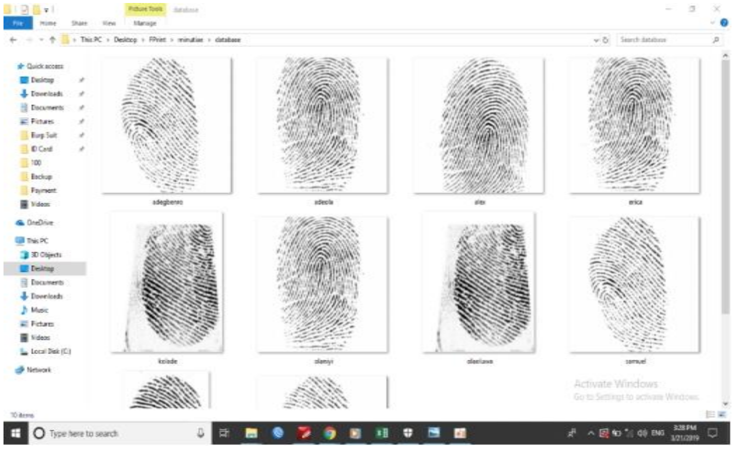
Prompt: Fingerprint scanner, scaning fingerprint

Status: Scanning Completed

Figure 3: Fingerprint enrollment process platform

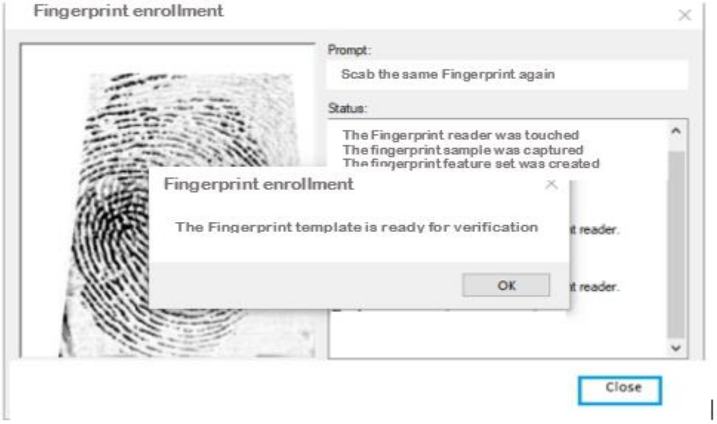
Figure 3 the steps involved in the fingerprint enrolment process, starting from image acquisition and pre-processing to feature extraction and template storage. The figure visually depicts how the fingerprint is captured and processed for future authentication.

Figure 4 shows how fingerprint templates are stored in the database with corresponding labels. It emphasizes the organized structure of the dataset used for matching during the verification process.



This PC › Desktop › FPrint › minutiae › database

Figure 4: Template in the database



Fingerprint enrollment

Prompt: Scab the same Fingerprint again

Status:
The Fingerprint reader was touched
The fingerprint sample was captured
The fingerprint feature set was created

Fingerprint enrollment

The Fingerprint template is ready for verification

Figure 5: Fingerprint enrolment process

Figure 5 illustrates the pre-verification interface, where a user's fingerprint is scanned and the system prepares for matching. It demonstrates the user interaction phase before the system performs authentication.

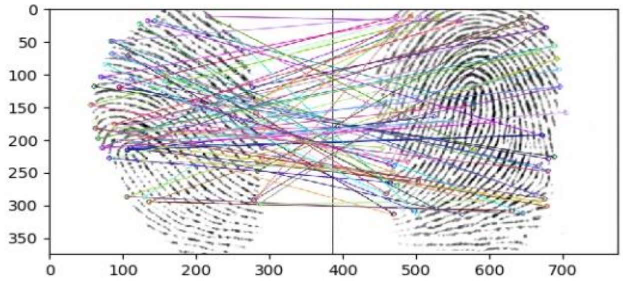
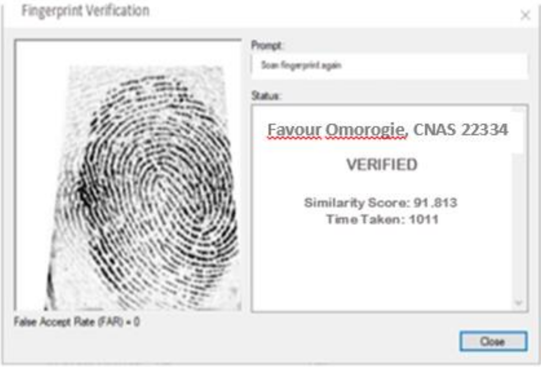


Figure 6: Matching processing stage

Figure 6 highlights the system's matching process, where a newly scanned fingerprint is compared to stored templates. It shows how the system evaluates the similarity score between the query image and the stored template to determine a match.



Prompt: Scan fingerprint again

Status:

Favour Omorogie, CNAS 22334

VERIFIED

Similarity Score: 91.813
Time Taken: 1011

False Accept Rate (FAR) = 0

Figure 7: Verification page

This figure 7 shows the verification interface, where the system provides feedback on whether the scanned fingerprint matches the stored template. It visualizes the result of the authentication process, confirming the user's identity if a match is found.

Table 2: Matching scores

Template Image	Query Image	Similarity Score	Time Taken (ms)
Fprint 1	Fprint 1	90.047	1014
Fprint 2	Fprint 2	93.236	1044
Fprint 3	Fprint 3	91.354	1017
Fprint 4	Fprint 4	89.125	1006
Fprint 5	Fprint 5	92.812	1006
Fprint 6	Fprint 6	97.445	1000
Fprint 7	Fprint 7	89.817	1032
Fprint 8	Fprint 8	95.993	1035
...	...	...	...
User 150	User 150	96.517	1063

Table 2 shows the similarity scores and processing times (in milliseconds) for various fingerprint queries compared to stored template images. The similarity score indicates the degree of match between the query image and the template, with higher scores reflecting better matches. Processing time refers to the time taken to complete the fingerprint matching process for each query.

Table 3: The comparative data for the three fingerprint recognition methods

Method	Recognition Accuracy (%)	Processing Time (milliseconds)
Minutiae-based	88.00	1200
Pattern-based	85.00	900
Pseudo Zernike Moments (PZMs)	91.813	1011

Table 3 and figure 8 compares the recognition accuracy and processing times of three fingerprint recognition methods: Minutiae-based, Pattern-based, and Pseudo Zernike Moments (PZMs). The recognition accuracy is expressed as a percentage, indicating the effectiveness of each method, while the processing time is given in milliseconds, showing the speed of each approach. The table highlights the trade-offs between accuracy and processing time across the methods.

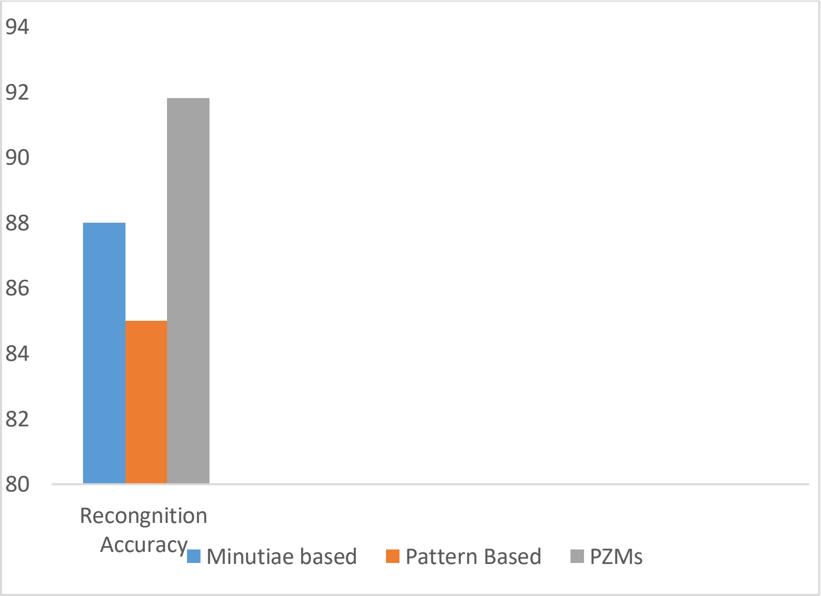


Figure 8: Bar chart showing recognition accuracy of the three methods

Discussion

The results provide a clear comparison of the three fingerprint recognition methods: Minutiae-based, Pattern-based, and Pseudo Zernike Moments (PZMs), highlighting their respective performance in terms of recognition accuracy and processing time. However, a deeper exploration of the trade-offs between recognition accuracy and processing time is necessary to understand the implications for practical applications.

In terms of **recognition accuracy**, the PZMs method outperforms the others, achieving 91.813 %, while the Minutiae-based method reaches 88% and the Pattern-based method 85%. This suggests that PZMs are better suited for applications requiring high precision, as they offer more detailed feature extraction and are less affected by distortions, such as noise or changes in image quality. However, this comes with a cost in terms of **processing time**. While the Pattern-based method is the fastest at 900 milliseconds, its lower accuracy makes it less desirable for high-security environments. On the other hand, the Minutiae-based method, despite its solid accuracy, suffers from a longer processing time (1200 milliseconds), which may limit its usability in real-time applications.

The PZMs method, with a processing time of 1011 milliseconds, offers a **balance** between accuracy and efficiency. This moderate processing time, combined with high recognition accuracy, makes PZMs a strong candidate for use in systems that require both reliability and reasonable speed, such as examination security systems.

Conclusion

The study demonstrated the effectiveness of a fingerprint recognition system using pseudo zernike moments (PZMs) in enhancing examination integrity by preventing impersonation and fraud. The system achieved a recognition accuracy of 91.81 %, outperforming minutiae-based and pattern-based techniques. It also achieved an overall recognition rate of 98.67 %, with a false rejection rate of 0 % and failure to enroll rate of 1.33 %. This highlighted the scalability and privacy benefits of PZMs-based biometric systems.

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Recommendations and suggestions for further studies

Educational institutions should adopt fingerprint biometrics to enhance exam integrity and reduce impersonation, while implementing strong encryption and privacy measures to protect sensitive data. Advanced techniques like Pseudo Zernike Moments (PZMs) should be explored for improved recognition accuracy in noisy environments. Further studies should focus on optimizing PZMs for computational efficiency, integrating machine learning techniques for enhanced recognition, and comparing various biometric modalities. Additionally, research should develop privacy-preserving biometric systems and examine user acceptance and ethical implications to ensure successful implementation of biometric technologies in examination security.

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