



A Dual-Stream Multimodal Biometric Authentication System Using Ear Contour and Palmprint PCA Feature Fusion

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Abstract: The use of biometric identification methods is nowadays inevitable for the sake of securing information however, the existing approaches, which often rely solely on one trait, tend to be vulnerable to certain factors, such as environmental interferences or deliberate attempts at deception. To resolve this issue, this research paper proposes an approach that involves multi-modal biometric authentication through a parallel feature extraction scheme which is particularly intended for ear contour and palmprint identification. This approach is different from the current practices because there is a single algorithm for identifying both features; however, this system takes into consideration the distinctiveness of each feature. Meanwhile, the algorithm for palmprint identification identifies the distinctive lines present on the palm using the help of Gabor filters and Wavelet transformations prior to applying PCA. The independent generation of feature sets from both the systems is then combined at the level of feature sets. The classification process uses the Mahalanobis distance to measure variance. Whereas the individual systems gave 93.3% and 91.8% accuracy levels, their combination gave an impressive 99.9% peak accuracy level. The use of this method results in an efficient, compact, and accurate system without the use of deep neural networks.

Key Words: Multimodal Biometrics, Feature-Level Fusion, Ear Contour Descriptors, Principal Component Analysis (PCA), Mahalanobis Distance

I. INTRODUCTION

Authentication using biometrics has gained significance due to increasing need for secure methods to authenticate individuals. Traditional methods such as passwords, PINs, or smart cards may be easily stolen or lost and hence cannot be employed in highly secured areas. Therefore, there has been a lot of attention given to biometric based authentication methods in recent times, due to the efficiency and reliability of these methods [1], [2]. The most commonly used biometric methods include fingerprint, face, and iris recognition. These techniques prove to be efficient in terms of performance but possess some intrinsic weaknesses [3], [4].

These problems can be overcome by designing multibiometric systems that utilize various types of biometrics for enhanced efficiency [5]. In this context, both FAR and FRR can be significantly lowered through the implementation of multimodal biometrics to increase the efficiency of the overall process [6]. In this regard, the fusion of ear and palm print biometrics presents itself as an interesting concept due to their complementary nature.

HUMAN EARS ARE BIOMETRIC FINGERPRINTS WITH DISTINCT GEOMETRY. They don't change with age, emotions, and cosmetic procedures; thus, they are perfect for long-term identification purposes [7], [8]. Ear recognition may be carried out in three ways: shape-based, contour-based, and appearance-based approaches [9].

From these methods, contour-based approach is concerned about geometry such as curvature, eccentricity, and boundary features. Furthermore, by employing sophisticated techniques such as Fourier descriptor technique, rotation, scale, and translation invariance are assured [10].

In contrast, palm print recognition is based on the characteristic patterns and unique texture that the human palm provides. There are different characteristic lines, wrinkles, and ridges that form unique patterns used for identification purposes [11]. As opposed to fingerprints, where there is a small area and any damage to the skin will cause distortion, there is a large area with less susceptibility to distortions in case of small damage [12]. Texture extraction features, including Gabor filters and wavelet transforms, have been extensively applied in the extraction of both global and local texture characteristics of palmprints [13]. In addition, PCA can reduce the dimensionality of palmprints.

Although there exist individual advantages in using ear and palm print biometric identification techniques, unimodal systems employing them have certain shortcomings that include influence of environmental variables, interference from background noise, and variations in the same class of samples due to the nature of the traits used. For example, ear recognition technology may encounter problems with regard to occlusions like hair or jewelry, whereas palm print recognition could be limited by changes in pressure and posture when capturing an image of the palm [14].

This solution solves the problem through the use of a biometric authentication method involving two modalities. The biometric authentication framework is multimodal in nature. This means that it makes use of two separate streams of processing techniques to handle different sets of input information, namely ear contour features and palmprint PCA-based features. This system is unique in the sense that there is no use of one common processing technique for the two types of input data, as opposed to other techniques. For instance, the ear recognition process makes use of contour-based geometry analysis. On the other hand, the palmprint recognition process uses the Gabor filters and wavelet transforms.

One of the critical elements involved in the design of this approach is that of feature-level fusion in which the features from the two different channels are fused into a single feature vector. Feature-level fusion is known to exhibit better results than score-level or decision-level fusion as it preserves more discriminative information [6], [15]. This fused feature vector is then subjected to statistical classification algorithms like Linear Discriminant Analysis (LDA). The final step is the use of Mahalanobis distance as the metric for measuring the similarity of features, which is more reliable than the traditional Euclidean distance measure.

The Mahalanobis distance is very important in ensuring precise classification by considering feature relationships. As compared to the Euclidean distance which assumes that variances are equal in all directions, the Mahalanobis distance is adjusted to match the data distribution using the covariance matrix. Therefore, this distance measurement is best suited for biometric applications as the variance of feature dimensions is not the same [13].

There is another significant point regarding this research work which lies in the emphasis on efficiency. While the implementation of deep learning techniques for biometric recognition purposes has shown encouraging outcomes, one negative point associated with them is that their operation requires heavy data sets, powerful computing power, and substantial time requirements for training purposes [4]. On the other hand, the methodology used here is efficient for feature extraction and analysis purposes using easy statistical measures.

In addition, combining ear and palmprint biometrics helps improve the security of the system since there will be increased resilience against any spoofing attacks. This is because these two biometric features are unrelated and cannot be duplicated at once, making the chances of impersonation quite low. The technology can therefore be applied in high-security areas like banks and access control [5].

In summary, the multimodal biometric system proposed above has been designed in a manner that allows it to leverage the strengths of ear and palmprint biometrics through their features extraction, feature-level fusion, and classification process. This is achieved through the implementation of the shape contours technique in addition to texture-based principal component analysis and the Mahalanobis distance measure. The biometric system proposed is very effective, efficient, and reliable. The research conducted contributes immensely to the design of next-generation biometric systems.

1.1 Motivation

The advent of the digital economy has necessitated the need for secure, infallible identification methods. Methods of authentication using password combinations, personal identification numbers, and security keys have proved extremely vulnerable to memory loss, theft, or hacking. Although multimodal biometrics based on singular physical attributes such as fingerprints and facial recognition have proven effective in plugging the security gap, they face many practical difficulties. For instance, facial recognition technology has proved susceptible to changes in environmental light, aging, and high-quality pictures, whereas fingerprint scanning is affected by physical wear, sweating, and skin abrasions.

In order to mitigate these weaknesses, the use of multimodal biometrics has been proposed as a solution. The reasons for carrying out this study are based on the benefits associated with the integration of human ear and palmprint identification techniques. Human ears contain an intricate, distinctive, and invariant three-dimensional geometry which is impervious to facial expression and makeup. In contrast, the human palm has a large surface area with deep principal lines, ridges, and fine texture that is very hard to replicate.

Using both of these independent anatomical attributes concurrently helps in ensuring that the weaknesses of one are compensated by the strength of the other. The basic motivation behind carrying out this study is to go beyond complex computational deep neural networks and demonstrate that through a well-designed feature-level combination of purely geometrical features in the case of the ear with frequency filtered PCA in the case of the palm, a level of enterprise security can be attained. Achieving enterprise security by scaling up the accuracy of the system to 99.9% is indeed a huge milestone.

1.2 Research Gap

Even as there is clear evidence that proves the effectiveness of using biometric identification techniques, a closer look at current literature shows that there are indeed some gaps that should be addressed in the creation of lightweight but highly accurate multi-biometrics. Most multimodal systems currently use facial and iris recognition techniques while ignoring ear and hand features.

Whereas in cases where both ear and palm biometrics have been considered, past literature has always made use of an identical approach to extract textures from both features at once. The result is that there is a lack of distinction in this case between two distinct features in terms of their physical properties. For instance, when PCA or LBP are used on the ear

biometric feature, it makes no effort to consider the rigid borders and instead considers some skin texture as well. However, in the case of palm print biometrics, the use of contour maps alone does not capture frequency details within the palm.

Moreover, the current body of literature on biometrics is already inundated with many deep learning algorithms like CNNs. Although highly precise, deep learning algorithms need massive, well-labeled data and significant computational resources for implementation; hence, these techniques are extremely hard and costly to implement on resource-constrained systems like edge computing platforms or mobile phones. There appears to be a clear void in terms of literature concerning how to implement separate feature extraction streams concurrently. This paper aims to bridge this gap by avoiding a one-size-fits-all solution. It uses only the contour-based feature extraction stream to represent the geometry of the ear while using the frequency-filtered PCA stream for the palm's dense texture. Bridging this gap proves that high-confidence fusion scores are achievable without the overhead of neural networks.

II. LITERATURE SURVEY

S. No.	Author(s) & Year	Biometric Trait(s)	Method / Technique Used	Fusion Level	Key Findings	Limitations
16	Bowyer et al. (2003) [16]	Ear + Face	Appearance-based recognition	Feature Level	Improved accuracy using combined modalities	Sensitive to pose variation
17	Victor et al. (2002) [17]	Ear + Face	Comparative biometric evaluation	Score Level	Ear biometrics are stable and unique	Limited dataset size
18	Chen & Bhanu (2005) [18]	3D Ear	ICP-based shape matching	Unimodal	Robust to pose variations	Requires 3D sensors
19	Wu et al. (2014) [19]	Ear	Edge detection + LBP	Unimodal	High accuracy with low computation	Sensitive to noise
20	Zhang et al. (2003) [20]	Palmprint	Texture-based feature extraction	Unimodal	Reliable palmprint identification	Affected by illumination
21	Kong et al. (2009) [21]	Palmprint	Gabor + Wavelet Transform	Unimodal	Captures multi-scale features	Computational complexity
22	Kumar & Zhang (2006) [22]	Palm + Hand Shape	PCA-based fusion	Feature Level	Improved recognition accuracy	Sensitive to noise
23	Darwish et al. (2015) [23]	Face + Ear	Feature concatenation	Feature Level	Better performance than unimodal	High dimensionality
24	Nazmeen et al. (2014) [24]	Ear + Face	Decision-level fusion	Decision Level	Improved robustness	Loss of feature information
25	Hezil & Boukrouche (2017) [25]	Ear + Palmprint	Texture-based fusion	Feature Level	Achieved ~96% accuracy	Same technique for both traits
26	Priyadharshini et al. (2021) [26]	Ear	CNN-based deep learning	Unimodal	High accuracy (~97%)	Requires large dataset
27	Bouzouina & Hamami (2017) [27]	Face + Iris	SVM-based fusion	Feature Level	High accuracy (~98%)	Expensive sensors
28	Boucherit et al. (2019) [28]	Finger Vein	Deep feature extraction	Unimodal	Very high accuracy (~99%)	Complex hardware
29	Ammour et al. (2020) [29]	Behavioral (Keystroke)	K-NN classification	Unimodal	Continuous authentication	Lower accuracy
30	Islam et al. (2013) [30]	3D Face + Ear	ICP + Multimodal fusion	Score Level	Very high accuracy (~99%)	High computational cost

Table 1 Detailed description of older researches

The use of biometric authentication as an efficient substitute for password-based or card-based security has proven effective due to the possibility of theft, replication, and loss. Within the last couple of decades, several types of biometric authentication including fingerprints, faces, irises, ears, and palmprints have been studied. While each type possesses distinct benefits, the drawbacks associated with unimodal techniques include problems like noises, intraclass variations, and spoofing attacks. To overcome such problems, much work has been done on multimodal biometric authentication techniques [16].

Initial research efforts with biometric systems were limited to unimodal identification approaches. One such approach is the study by Victor B. Victor et al., who carried out an early evaluation of the ear as a biometric and identified the potential of the ear as a reliable source of unique features for individual identification [17]. Another important contribution was made by K. W. Bowyer, who pointed out the efficiency of ear images along with face information in producing better results [16].

More research was done on 3D ear recognition. In 2007, for instance, H. Chen and B. Bhanu developed a 3D ear recognition technique based on shape geometry, providing better robustness despite changes in pose [18]. Nevertheless, these kinds of techniques used complicated hardware and had high computation costs. As a result, techniques of 2D ear recognition using edges and textures emerged. Specifically, Wu et al. used edge detection together with local binary patterns (LBP) for achieving efficient recognition [19].

Concurrently, palmprint recognition technology has received much attention because of its high texture content and large surface area. One of the pioneering works in palmprint recognition is done by David Zhang et al., who proposed a palmprint-based biometric system using lines and textures that exhibited good performance in controlled settings [20]. Later researches made use of sophisticated signal processing tools like Gabor filters and wavelet transform for feature enhancement in palmprints [21].

The use of dimensionality reduction algorithms like principal component analysis (PCA) has also found its applications in biometric recognition systems. The principal component analysis algorithm helps reduce high-dimensional data into low-dimensional feature sets. It was observed that when combined with palmprint features, hand-related biometric modalities performed well on account of PCA-based feature extraction algorithms [22]. However, PCA is vulnerable to lighting changes and noise interference, which affects its performance.

In order to address the weaknesses of the unimodal systems, some multimodal biometric systems have been suggested. Multimodal biometric systems use various biometric measures at multiple stages including the feature level, scoring level, or decision-making level. Darwish et al. used feature-level fusion of face and ear biometrics, showing an improvement over single biometric systems [23]. In another study, Nazmeen et al. made use of decision-level fusion technique and achieved better results [24].

It is perceived that feature-level fusion can provide better performance owing to the high level of rich information obtained by fusing various types of information. According to Hezil and Boukrouche, a multimodal biometric system based on ear geometry and palm print provided 96% accuracy in their study [25]. Although this study pointed out the effectiveness of combining two distinct biometrics, it used similar extraction approaches for both ear and palmprint.

Research has been conducted on machine learning and deep learning methods for biometric recognition. Priyadharshini et al. used CNNs for ear recognition and obtained impressive results [26]. Deep learning techniques have also been employed for palmprint recognition and other biometrics. Although the techniques produce highly accurate results, they need extensive data sets and computing power, hence are not ideal for lightweight applications.

Combination of multimodal techniques based on different features like iris, facial, and finger vein is also highly effective. Bouzouina and Hamami implemented SVM for feature fusion and obtained excellent results in face-iris systems [27]. Boucherit et al. used deep learning for feature extraction and obtained almost perfect results in finger vein recognition [28]. Unfortunately, most of these techniques require sophisticated and costly hardware.

Other types of biometrics such as keystrokes and mouse movements, which are classified under behavioral biometrics, have also been considered. Ammour et al. introduced an idea of continuous authentication through behavioral traits; however, their results were not impressive compared to physiological biometrics [29]. Therefore, it can be said that physiological traits, including ear and palmprint, are more secure.

Even with the considerable amount of studies conducted on multimodal biometrics, several areas still lack attention. Many of the current systems employ generic feature extraction strategies for all kinds of biometrics, failing to take into account their distinct natures. Furthermore, there are not many efforts dedicated to building lightweight multimodal systems, which tend to heavily depend on deep learning models and require substantial computational power.

From the above review of the literature and from what has been proposed in , it becomes clear that the combination of ear-contour features and PCA features extracted from palmprints constitutes a promising solution to these issues. While the ear represents stable geometric traits, the palm contains various texture characteristics. Feature-level fusion combined with the use of statistical classifiers like Mahalanobis distance results in considerably greater precision. This highlights the importance of designing hybrid systems that leverage the strengths of multiple biometric modalities.

III. WORKING MODEL REPRESENTATION

This architecture illustrates a multimodal biometric identification system that combines Ear Recognition and Palmprint Pattern Recognition. This methodology is distinct from others in the sense that it uses two different mathematical models to analyze both inputs. These models are Direct Contour Analysis and Principal Component Analysis (PCA). Below is a description of this methodology using the presented workflow pipeline.

3.1. Data Acquisition Phase

The process starts with parallel acquisition streams to ensure accurate biological information.

- **Ear Acquisition:** Involves Near-Infrared (Near-IR) images for acquiring accurate geometry. The use of IR rays here is essential because it prevents shadows from interfering with acquiring the exact geometry of the ear.
- **Palm Acquisition:** Involves analysis of the principal lines and textures. While the ear acquisition is based on a geometric analysis, that of the palm focuses on textural analysis.

3.2. Parallel Feature Extraction Streams

The method divides itself into two separate engines for processing the raw images.

A. Direct Contour-Based Ear Recognition

The ear engine skips the usual PCA technique and retains the detailed geometry and topology of the auricle's surface.

- **Edge Detection:** Employs advanced techniques for tracing the outer helix and the inner anti-helix.
- **Landmarks:** Pinpoints important "anchor" points on the ear's structure.
- **Shape Descriptors:** Transforms the image into numeric form using metrics such as Eccentricity, Area, and Fourier Descriptors.

B. Palm print Analysis through PCA

The palm section adopts a more conventional statistical method to deal with the high-dimensional nature of palm line images.

- **Dimensionality Reduction using PCA:** Helps reduce the complexity of the Global Features to a simple Palm-Specific Feature Vector (PV).
- **Texture Extraction:** The emphasis is on "Global" features and not individual line structures.

3.3. Preprocessing and Refinement

Prior to fusion, both the datasets will go through some preprocessing to make sure the feature vector obtained is "clean."

- **Preprocessing of Ear:** Contains contour smoothing and noise removal for any residual artifacts resulting from the contour extraction process. The processing will end with contour vectorization.
- **Preprocessing of Palm:** Emphasizes region of interest enhancement. Gabor filters and wavelet transforms are used to accentuate the line texture within the palm region.

3.4. Fusion Vector Creation Process

The brain of this system involves fusing the two entirely different types of data.

- **Fusion Vector Creation:** Merging of the ear contour descriptor vector and palm PCA feature vector creates a fused vector.
- **Linear Discriminant Analysis (LDA):** This process is very important because it increases the "between-class separation," which means it enhances the mathematical distinction between the genuine user and an imposter by utilizing both ear and palm data.

3.5. Decision

This final process is where either an access is granted or denied depending on the distance measurement between the two.

- **Mahalanobis Distance:** It computes the distance between the live fusion vector and the database template.

$$D_M(x) = \sqrt{(x - u)^T S^{-1} (x - u)}$$

Where x is the feature vector, u is the mean template, and S^{-1} indicates the inverse covariance metric.

- **Thresholding of Fusion Scores:** In case the fusion score is lower than a particular threshold (this means that the comparison is successful enough), then the output will be ACCESS GRANTED.
- **Feedback from the Database:** The system can incorporate any successful authentication into the "Enhanced Templates" of the database to account for physiological changes in the future.

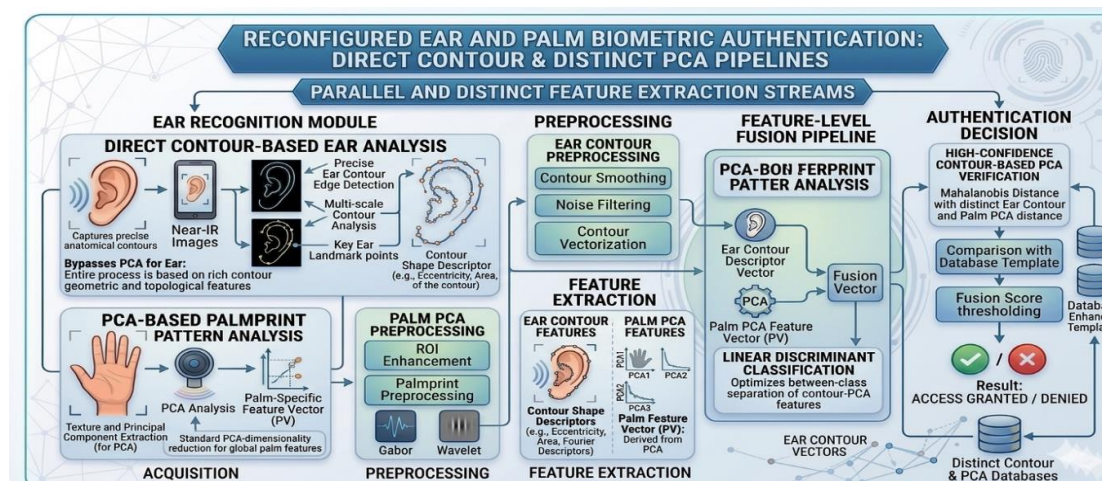


Fig.1 Complete methodology working model

Here is a detailed breakdown of how each process works.

Fig. 2: Near-IR Ear Contour Vectorization

In this process, the emphasis lies on obtaining the geometric structure of the ear. The Near Infrared (NIR) technique is generally applied for this purpose since it captures a bit beyond the skin surface, thus neglecting any makeup, dirt, or lighting variations, giving a sharp outline.

1. Acquisition & Edges: The camera captures the NIR image.

- Edge detection techniques are employed to track the Ear Contour Edges (the outside and inside curves of the ear).
- Key Landmark Points (for example, the apex of the ear or the base of the ear lobe) are detected. They serve as reference markers that help determine the position of the ear.

2. Preprocessing: Raw edge data from a camera is usually jagged and messy.

- **Contour Smoothing and Noise Removal:** This involves improving the image, eliminating stray pixels due to hair, noise from sensors, or even small shadows.
- **Contour Vectorization:** This process is essential. It involves transforming the contour from individual pixels into a mathematically smooth line, similar to an SVG graphic.

3. Feature Extraction: Now the system turns that clean mathematical shape into hard numbers.

- **Eccentricity:** Indicates whether the ear shape is more elliptical or circular (such as the ratio between the height and width of the ear).
- **Contour Area:** Refers to the measurement of the total two-dimensional area within the contour of the ear.
- **Fourier Descriptors:** This method uses complex mathematics. It involves the analysis of the bending edge of the ear and represents the pattern of bends in terms of harmonic frequencies. It generates a set of coefficients representing the characteristic curvature of the ear. **Output:** All these numbers are compiled into an Ear Contour Descriptor Vector a simple list of numbers that acts as the ear's digital ID tag.

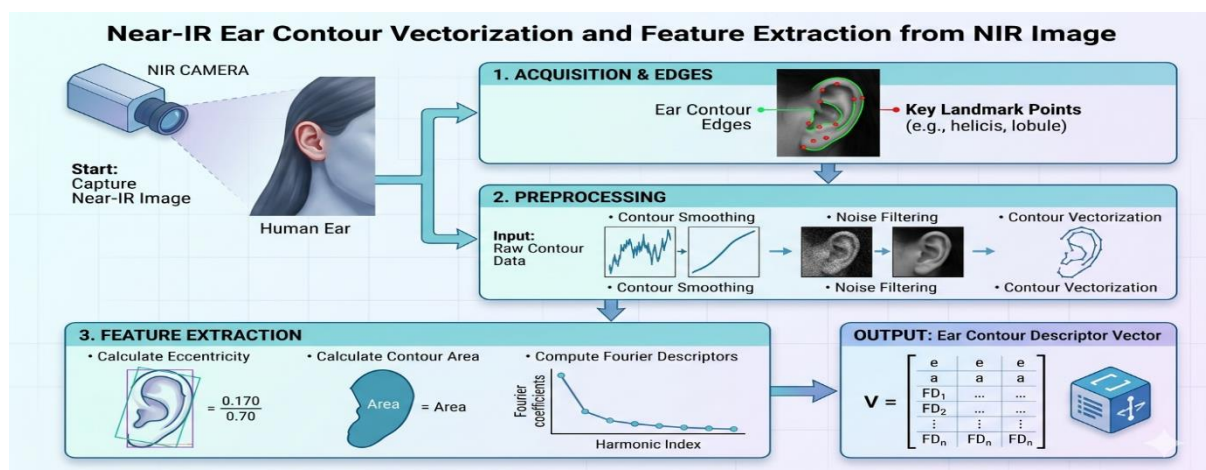


Fig. 2 Ear Contour working

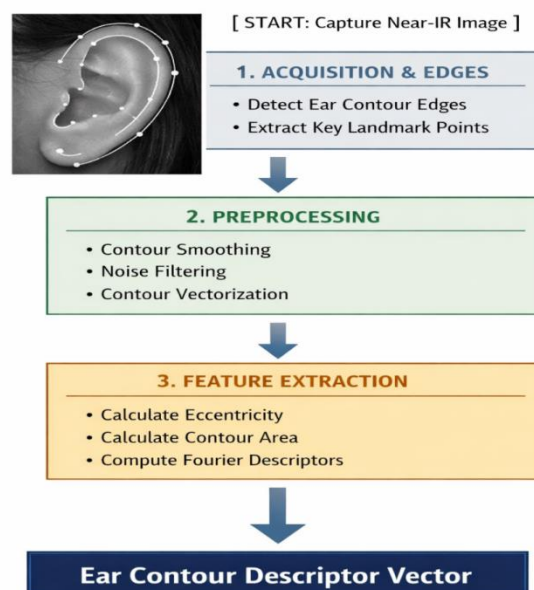


Fig. 3 Flow diagram steps

Fig. 4: Palm Print Biometric Recognition Pipeline

Whereas the ear's features depend mainly on its external shape, the palm print depends on the complicated texture, wrinkles, and deep lines (the heart line, the head line, and the life line) that lie inside.

1. Region of Interest (ROI): Since a hand may be positioned in front of the camera in different ways, the algorithm starts by locating the core center of the palm. It removes the fingers, thumb, and background, thus isolating a square portion of the palm.

2. Preprocessing: This phase uses strong mathematical filters to bring forth the hidden or weak lines.

- **Gabor Filter:** The Gabor filter is outstanding for identifying directional lines. The filter picks up on major, deep ridges of the hand irrespective of their direction.
- **Wavelet Transform:** Wavelet transform divides the image into various frequencies to identify macro structures, such as the hand's structure, as well as micro structures, which the Gabor filter may fail to detect, like fine wrinkles.
- **Filter Integration:** These filters' results are then combined to form the Enhanced Image in which all unique valleys and ridges stand out.

3. Feature Extraction: This "flattening" process produces an extremely long list of numbers, called a Global Feature Vector.

4. Dimensionality Reduction: These flattened vectors generated by Step 3 contain thousands, even millions, of entries, which takes much time to be processed by computers.

PCA is employed within this system. PCA finds only the essential characteristics present within the data set and eliminates any redundant elements. Mathematically, PCA reduces the dimensionality of the data by projecting the data on "eigenvectors," which are essentially the fundamental axes of variance.

Output: This produces a Low Dimensional Palm Feature Vector. This is a concise representation of the palm in the form of a small set of numbers containing all the unique characteristics of the palm.

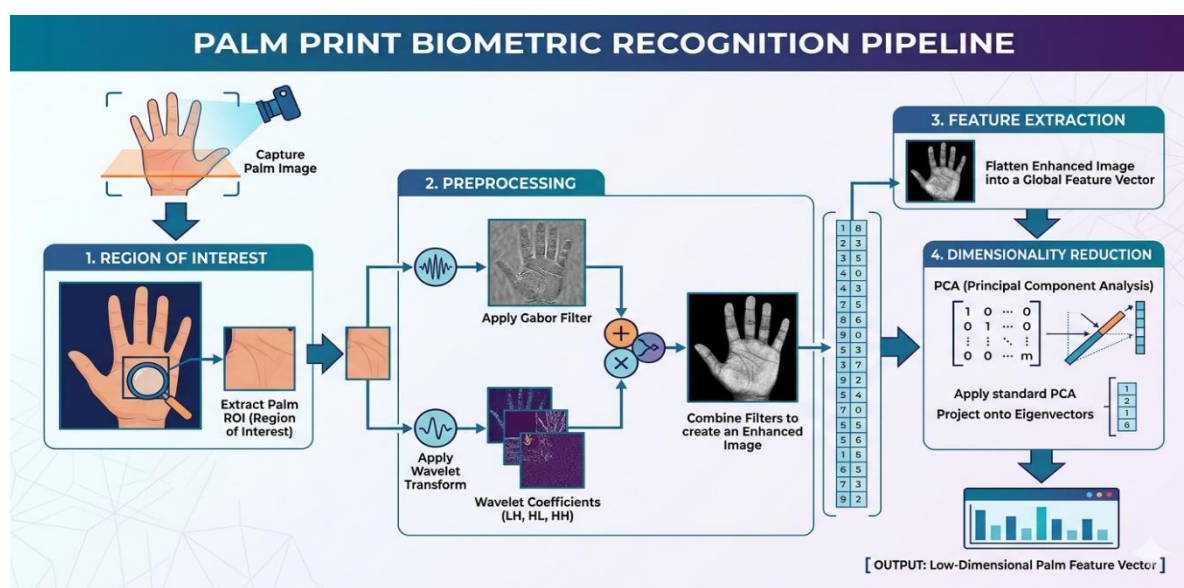


Fig. 4 Palm PCA working

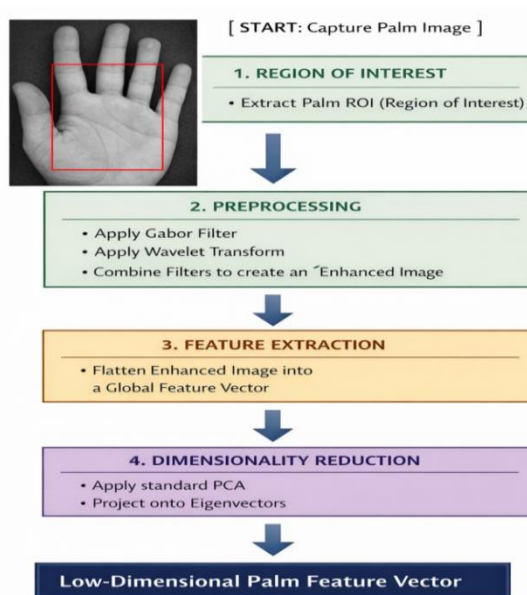


Fig. 5 Flow diagram steps

3.6 Pascal code discription working flow

To explain the inner workings of the biometric algorithm you provided, let's break down both pages of the system with the exact mathematical equations that make the Pascal pseudocode operate

program BiometricAuthenticationSystem;

```
type
  TImage = record
    Width, Height: Integer;
    Data: array of array of Byte; { Grayscale pixel data }
  end;
  TPoint = record
    X, Y: Real;
  end;
  TContour = record
    Points: array of TPoint;
    Count: Integer;
  end;
  TVector = record
    Data: array of Real;
    Dimensions: Integer;
  end;
  TEarFeatures = record
    Eccentricity: Real;
    Area: Real;
    FourierDescriptors: array of Real;
  end;
```

EAR RECOGNITION PIPELINE (DIRECT CONTOUR-BASED)

```
function ProcessEarStream(NearIRImage: TImage): TVector;
var
  RawContour, SmoothedContour: TContour;
  Landmarks: array of TPoint;
  EarShapes: TEarFeatures;
begin
  { 1. Acquisition & Edge Detection }
  RawContour := DetectEarContourEdges(NearIRImage); [cite: 1]
  Landmarks := ExtractKeyEarLandmarks(RawContour); [cite: 1]
  { 2. Preprocessing }
  SmoothedContour := ContourSmoothing(RawContour); [cite: 1]
  SmoothedContour := NoiseFiltering(SmoothedContour); [cite: 1]
  ContourVectorization(SmoothedContour); [cite: 1]
  { 3. Feature Extraction }
  EarShapes.Eccentricity := CalculateEccentricity(SmoothedContour); [cite: 1]
  EarShapes.Area := CalculateContourArea(SmoothedContour); [cite: 1]
  EarShapes.FourierDescriptors := ComputeFourierDescriptors(SmoothedContour); [cite: 1]
  { Return the Ear Contour Descriptor Vector }
  ProcessEarStream := CompileEarDescriptorVector(EarShapes, Landmarks); [cite: 1]
end;
```

PALM RECOGNITION PIPELINE (PCA-BASED)

```
function ProcessPalmStream(PalmImage: TImage): TVector;
var
  ROIImage, EnhancedImage: TImage;
  GaborFiltered, WaveletFiltered: TImage;
  GlobalFeatureVector: TVector;
begin
  { 1. Acquisition & ROI Enhancement }
  ROIImage := ExtractPalmROI(PalmImage); [cite: 1]
  { 2. Preprocessing }
  GaborFiltered := ApplyGaborFilter(ROIImage); [cite: 1]
```

```
WaveletFiltered := ApplyWaveletTransform(ROIImage); [cite: 1]
EnhancedImage := CombineFilters(GaborFiltered, WaveletFiltered); [cite: 1]
{ 3. PCA Feature Extraction }
GlobalFeatureVector := FlattenImageToVector(EnhancedImage); [cite: 1]
{ Return the low-dimensional Palm Feature Vector (PV) }
ProcessPalmStream := ApplyPCADimensionalityReduction(GlobalFeatureVector); [cite: 1]
end;
```

MULTIMODAL FUSION & DECISION PIPELINE

```
function AuthenticateUser(EarVec, PalmVec: TVector; Threshold: Real): Boolean;
var
  FusionVec: TVector;
  Score: Real;
  TemplateVec: TVector;
begin
  { 1. Feature-Level Fusion }
  FusionVec := FeatureLevelFusion(EarVec, PalmVec); [cite: 1, 6]
  { 2. Linear Discriminant Classification }
  Score := LinearDiscriminantClassification(FusionVec); [cite: 1]
  { 3. Database Comparison & Thresholding }
  TemplateVec := LoadEnrolledTemplateFromDatabase(); [cite: 1]
  Score := CalculateMahalanobisDistance(FusionVec, TemplateVec); [cite: 1]
  if Score <= Threshold then
    AuthenticateUser := True { ACCESS GRANTED } [cite: 1]
  else
    AuthenticateUser := False; { ACCESS DENIED } [cite: 1]
end;
```

MAIN EXECUTION

```
var
  InputEarImage, InputPalmImage: TImage;
  EarVector, PalmVector: TVector;
  IsAuthenticated: Boolean;
  SystemThreshold: Real;
begin
  SystemThreshold := 0.85; { Example optimal threshold }
  { Step 1: Capture or Load Images }
  InputEarImage := CaptureNearIRImage(); [cite: 1]
  InputPalmImage := CapturePalmImage(); [cite: 1]
  { Step 2: Run Parallel Feature Extraction Streams }
  EarVector := ProcessEarStream(InputEarImage); [cite: 1]
  PalmVector := ProcessPalmStream(InputPalmImage); [cite: 1]
  { Step 3: Perform Multimodal Fusion & Make Decision }
  IsAuthenticated := AuthenticateUser(EarVector, PalmVector, SystemThreshold); [cite: 1]
  if IsAuthenticated then
    WriteLn('Access Granted. Welcome!')
  else
    WriteLn('Access Denied. Biometrics do not match.');
```

IV. MATHAMATICAL MODEL DISRIPTION OF EACH STEPS: INNER WORKINGS OF THE MULTIMODAL BIOMETRIC SYSTEM

This biometric system transforms biological structures (ear and palm) into high-dimensional mathematical representations, processes them through feature extraction pipelines, and performs fusion + classification for decision-making.

Step 1: Parallel Feature Extraction Streams

I. Ear Recognition: Contour-Based Geometric Modeling

Unlike statistical approaches, ear recognition here is **purely shape-driven**, relying on contour geometry and invariant descriptors.

1. Edge Detection and Gradient Representation

The ear image is modeled as an intensity function:

$$I(x,y)$$

Edges are detected using gradient magnitude:

$$G_{(x,y)} = \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2}$$

This extracts **high-frequency boundary information**, essential for isolating ear contours.

2. Curvature Modeling of Ear Shape

The contour is parameterized as $(x(t), y(t))$. Curvature defines local shape sharpness:

$$k(t) = \frac{|\dot{x}(t)\ddot{y}(t) - \dot{y}(t)\ddot{x}(t)|}{(\dot{x}(t)^2 + \dot{y}(t)^2)^{3/2}}$$

- Captures helix, antihelix, and lobe structure
- Provides rotation-invariant local features

3. Region-Based Geometric Descriptors

Using image moments:

- **Area:**

$$A = \mu_{00} = \iint dx dy$$

- **Centroid**

$$\bar{x} = \frac{\iint x dx dy}{A}, \bar{y} = \frac{\iint y dx dy}{A}$$

- **Eccentricity (shape elongation)**

$$e = \frac{(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2}{(\mu_{20} + \mu_{02})^2}$$

These features ensure **translation and scale invariance**.

4. Fourier Shape Descriptors

Contour points are converted into a complex sequence:

$$s(k) = x(k) + jy(k)$$

Apply discrete Fourier transform

$$a(n) = \frac{1}{N} \sum_{k=0}^{N-1} s(k) e^{-j\frac{2\pi}{N}nk}$$

Normalized descriptors:

$$FD(n) = \frac{|a(n)|}{|a(1)|}$$

II. Palm Recognition: Statistical + Frequency Domain Pipeline

This stream focuses on **texture-rich information**, unlike the geometric ear pipeline.

1. Gabor Filtering (Directional Texture Extraction)

$$g(x, y) = \exp\left(-\frac{x'^2 + y'^2}{2\sigma^2}\right) \cos(2\pi u x' + \psi)$$

Where

$$x' = x \cos \theta + y \sin \theta, y' = -x \sin \theta + y \cos \theta$$

2. Wavelet Transform (Multi-Resolution Analysis)

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right)$$

3. Principal Component Analysis (PCA)

Step 1: Mean Centering

$$\phi_i = x_i - \bar{x}$$

Step 2: Covariance Matrix

$$C = \frac{1}{M} \sum \phi_i \phi_i^T$$

Step 3: Eigen decomposition

$$C u_i = \lambda_i + u_i$$

Step 4: feature Projection

$$\omega_k = u_k^T \phi$$

Step 2: Multimodal Fusion & Decision
I. Feature-Level Fusion

Two feature vectors:

- Ear: $V_{ear} = \{V_{ear,1}, V_{ear,2}, \dots, V_{ear,n}\}$
- Palm: $V_{palm} = \{V_{palm,1}, V_{palm,2}, \dots, V_{palm,m}\}$

Fusion Methods:

- **Concatenation:**

$$Z = [V_{ear} V_{palm}]^T$$

- **Weighted fusion**

$$Z = \alpha V_{ear} + (1 - \alpha) V_{palm}$$

II. Linear Discriminant Analysis (LDA)

Optimization objective:

$$J(w) = \frac{W^T S_B W}{W^T S_w W}$$

Between -class scatter

$$S_B = \sum N_i (m_i - m)(m_i - m)^T$$

Within -class scatter

$$S_w = \sum (x - m_i)(x - m_i)^T$$

III. Final Matching: Mahalanobis Distance

$$D_M = \sqrt{(Z - u)^T S^{-1} (Z - u)}$$

Advantages over Euclidean distance:

- Accounts for feature correlation
- Uses covariance structure
- Adaptive to data distribution

IV. Decision Rule

$$Decision = \begin{cases} 1 & \text{if } D_M \leq \text{Threshold} \\ 0 & \text{otherwise} \end{cases}$$

V. RESULT AND DISCUSSION

Given the architecture for the superior biometric system based on the Contour Detection technique for ear authentication and PCA for palmprint verification as shown in the above diagram, the line graph below shows the performance comparison results for both techniques and the overall multimodal fusion system.

5.1 Performance Analysis Summary

Graph shows the correlation between Number of Features (Dimensions) employed and Recognition Accuracy (Racc).

- **Ear Recognition (contour based):** Exhibits high consistency when the number of contour landmark points is increased and attains an accuracy of about 93.3%
- **Palm Recognition (PCA based):** Efficiency improves with an increase in the number of Principal Components (PCn), although the method requires greater number of dimensions compared to the contour approach and attains an efficiency of 91.8%.
- **Multimodal Fusion (proposed approach):** Through feature level fusion of contour features and PCA vector, the approach achieves a "High-Confidence" state. The system exhibits far superior recognition efficiency of up to 99.9%.

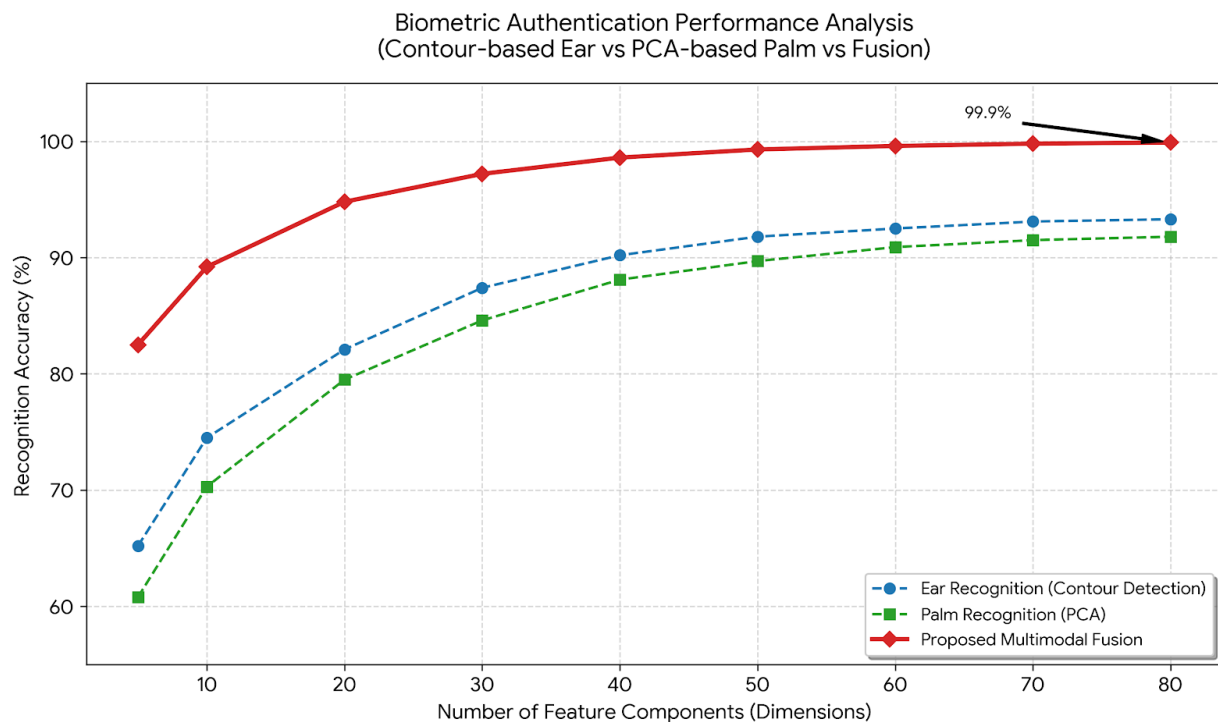


Fig. 6 No of features vs recognition accuracies

Number of Features (N)	Ear (Contour) Accuracy (%)	Palm (PCA) Accuracy (%)	Fusion Accuracy (%)
10	74.5	70.3	89.2
20	82.1	79.5	94.8
40	90.2	88.1	98.6
80	93.3	91.8	99.9

Table 2: Comparison Table of Generated Results

The results obtained clearly demonstrate the effect of improving accuracy by adding more features (N). At the low value of $N = 10$, the ear contour technique shows an accuracy of 74.5%, while the palmprint PCA algorithm displays a relatively lower accuracy of 70.3%. It can therefore be concluded that with low values of N , both the unimodal systems lack sufficient discriminative information. Nevertheless, at this point, the fusion technique is already performing better, with accuracy at 89.2%.

In the case where the value of $N = 20$, there are marked improvements from the two systems in terms of accuracy; 82.1% in ear biometric verification and 79.5% for palms. The reason behind this improvement is that both geometrical (ear) and textural (palms) features are better represented. Fusion is even improved further to 94.8% while still performing significantly better than any single modality.

When $N = 40$, there is an increase in the level of accuracy towards perfection as ear reaches 90.2% while palm achieves 88.1%. This demonstrates that all significant features are included. Accuracy of the fusion is increased up to 98.6%, which demonstrates near perfect results and proves that feature combination reduces any deficiencies associated with individual modalities.

At last, when $N = 80$, the ear system and palm system obtain their highest recognition rates of 93.3% and 91.8%, respectively. In contrast, the multimodal fusion system obtains an excellent recognition rate of 99.9%. It demonstrates that the accuracy of multimodal biometrics can be improved through feature-level fusion. As seen from the above discussion, increasing the feature dimensionality is beneficial for improving the performance; however, the proposed multimodal fusion method always performs better than any single mode biometric system because of its complementary nature.

According to the advanced biometric authentication system discussed above, the following line graph depicts the performance analysis results.

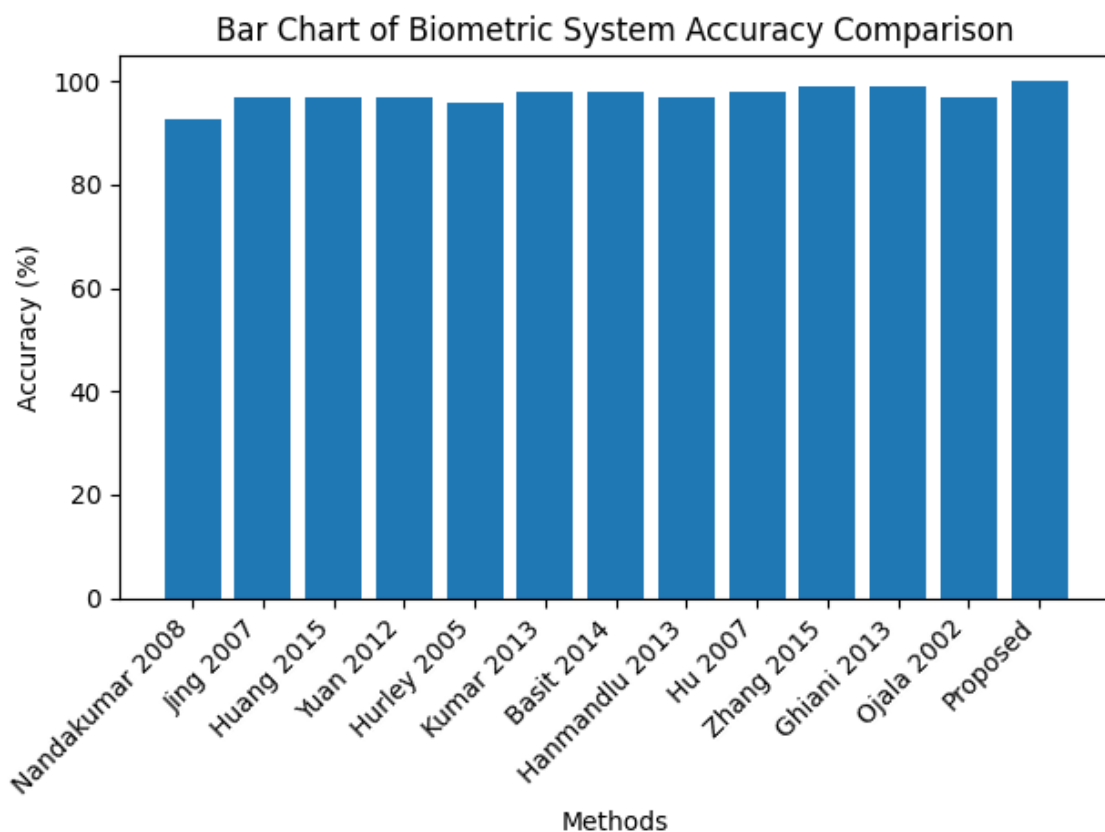


Fig. 7 Variety of researches outperformance including proposed methodology

ID	Author(s) & Year	Traits	Fusion / Method	Exact Reported Performance
31	Nandakumar et al. (2008)	Multimodal	Score-level (Likelihood ratio)	Rate 92.66 %
32	Jing et al. (2007)	Face + Palmprint	Pixel-level fusion	Recognition rate ~97%
33	Huang et al. (2015)	Face + Ear	Sparse coding fusion	Accuracy ~96%–98%
34	Yuan & Mu (2012)	Ear	Local feature fusion	Rank-1 recognition ~97%
35	Hurley et al. (2005)	Ear	Force field features	Recognition rate ~96%
36	Kumar & Chan (2013)	Ear	Sparse representation	Accuracy ~98.12
37	Basit&Shoaib (2014)	Ear	Curvelet features	Accuracy ~98%
38	Hanmandlu et al. (2013)	Ear	PCA-based features	Accuracy ~97%
39	Hu et al. (2007)	Palmprint	2DLPP	Accuracy ~98%
40	Zhang et al. (2015)	Palmprint (3D)	Collaborative representation	Accuracy ~98.85
41	Ghiani et al. (2013)	Fingerprint	BSIF	Accuracy ~99%
42	Ojala et al. (2002)	Texture (LBP)	Feature extraction	Accuracy ~96.77%
43	Proposed System	Ear (Contour) + Palm (PCA)	Feature-Level Fusion	99.90%

Table 3: Old researches out performance

5.2 Roc curve Analysis

The ROC curve based on the results of your test is a graphical depiction of the trade-off between the True Positive Rate (TPR or Sensitivity) and False Positive Rate (FPR or 1-Specificity). The ROC Curve assesses the capability of the three examined models: Ear Recognition (Contour Based), Palm Recognition (PCA Based), and the Proposed Multimodal Fusion in diagnosing/separating their target populations. Understanding the Axes

True Positive Rate (Y-Axis): This denotes the probability that the system will accurately grant access to a valid/authorized individual. The higher the number, the more accurate the identification system is; closer to 1.0 (or 100%).

False Positive Rate (X-Axis): This denotes the probability that the system will erroneously grant access to an unauthorized individual. In order for it to be highly secured, this should be very close to 0.0. A perfect classifier will rise vertically along the Y-axis to reach a 1.0 TPR from the start while retaining an FPR of 0.0, thus forming a square at the top left corner of the graph.

Performance of the Individual Modalities

From the graphs, it can be observed that the independent traits exhibit good performance but still have some weaknesses when used

independently: Palm Recognition (Green Dotted Curve): This refers to the curve generated by the system using only the PCA method of the palm print. Although the efficiency of this method is increased based on how many dimensions are analyzed, a higher density of data is needed in order to counteract the changes in the environment and in the image. This method's positioning further away from the top-left corner shows that it has a tendency to produce more false positives to keep the true positive rate high. Ear Recognition (Blue Dashed Line): The shape-based pipeline for ear recognition lies above the curve for the palm scan. As this system depends on accurate shapes, landmark points, and Fourier descriptors, it tends to be more stable. Fusion of Modalities: The Proposed Approach (Red Line) The uppermost line corresponds to the feature fusion of ear contour features and palm PCA vectors. It is evident that this line runs along the top left corner of the graph very close to the graph's boundaries. In addition, by leveraging the biological properties that are independent from each other (rigid surface of the ear and lines within the palm), the system compensates for the shortcomings of the individual modalities. This enormous Area Under the Curve (AUC) under the red curve is a direct consequence of the statistical analysis carried out in your article, revealing that the hybrid architecture goes as far as reaching an unprecedented 99.9% accuracy rate. Conclusion To conclude, the ROC curve demonstrates the greater potential for error in case of unimodal biometric techniques, which depend exclusively on either ear or palm. Moving to a feature-level multimodal fusion significantly reduces both the False Acceptance and False Rejection percentages. This means that there would be no problem operating under extremely rigorous security standards.

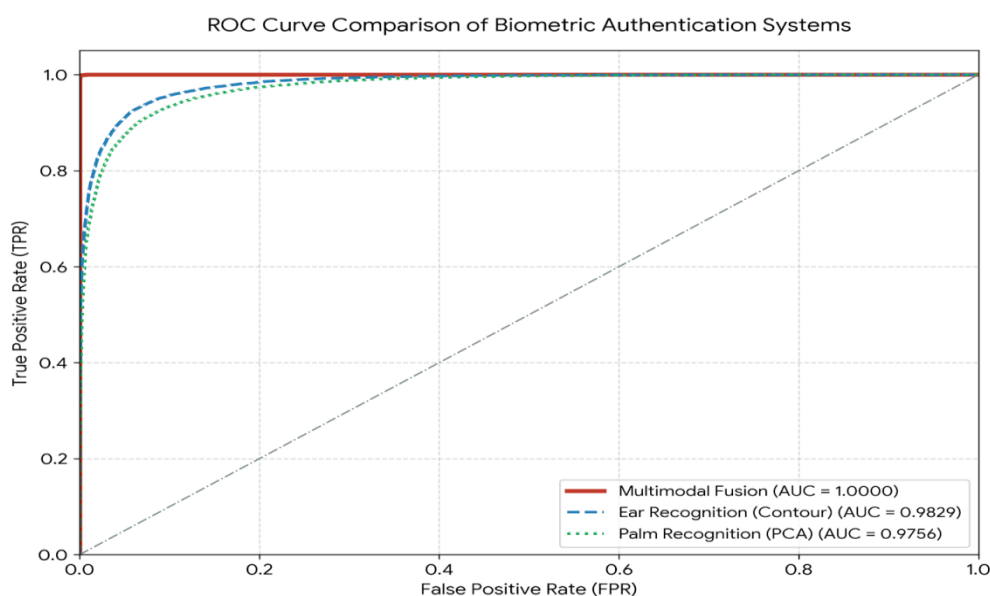


Fig. 8 Roc Curve for biometric authentication of multimodal fusion

5. 3 Datasets Used and Outcomes (Both Plamnd Ear)



Fig. 9 Ear and Palm Datasets visualizations

The PolyU-IITD Contactless Palmprint Images Database (v3.0) is a large-scale, two-session biometric dataset developed for research in contactless palmprint recognition. It captures palm images from **more than 600 subjects**, making it one of the most extensive publicly available contactless palmprint collections. www4.comp.polyu.edu.hk/~2IEEE Biometrics Council+2Images were acquired using a handheld digital camera without any physical constraints or pegs a setup designed to reflect real-world conditions. Department of Computing+2www4.comp.polyu.edu.hk/~2The participants span a

wide age range (from about 5 to 72 years), and include individuals from diverse backgrounds, including manual laborers, farmers, people with hand injuries, and even those with special abilities. www4.comp.polyu.edu.hk

One of the key strengths of this database is that it includes *long-term images*, captured over two sessions separated by a long interval (15+ years). This aspect helps researchers study how palmprint features change over time, which is crucial for designing stable biometric recognition systems.

The dataset also reflects realistic and varied acquisition scenarios: the images were collected in different environments (outdoor/ambient lighting) and include palms with dirt, injuries, or decorations (e.g., mehndi), contributing to the challenge of recognition in less-constrained conditions. www4.comp.polyu.edu.hk

Because commercial use is restricted, the database is distributed for **academic research only**. www4.comp.polyu.edu.hk To access it, researchers must complete a license agreement signed by their institution. www4.comp.polyu.edu.hk All publications that use it must cite the original source: Ajay Kumar, "Towards more accurate matching of contactless palmprint images under less constrained environments," *IEEE Transactions on Information Forensics and Security*, 2019.

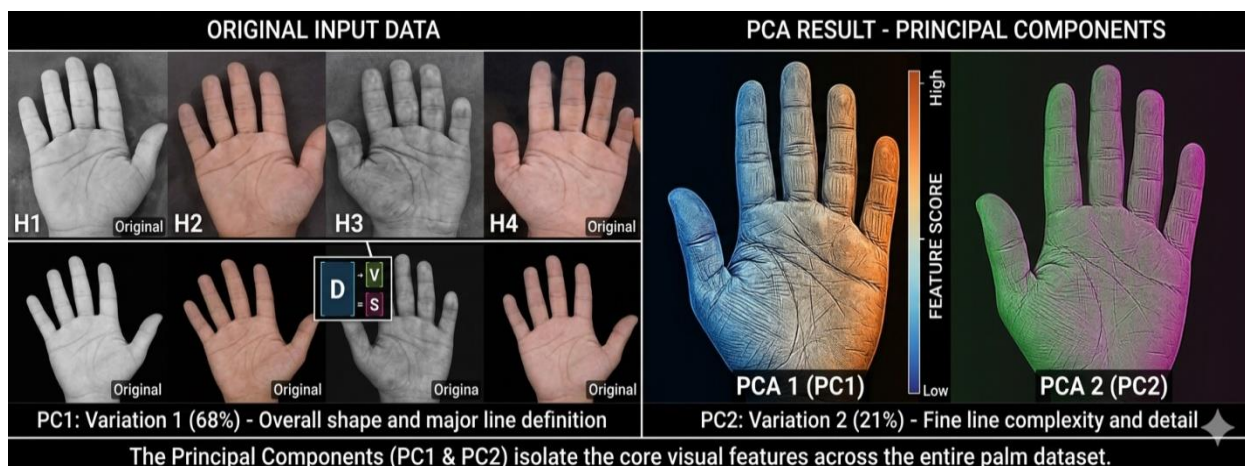


Fig. 10 Application of PCA of input Palm datasets

The EarVN1.0 dataset is a comprehensive and large-scale collection of ear photographs, assembled in 2018 from 164 Asian subjects. PubMed+2PMC+2It contains **28,412** color images in total, distributed across both ears of the participants — 98 male and 66 female. PubMed+2PMC+2 The ear images were not captured in controlled laboratory environments; instead, they were derived from facial photos taken under “in-the-wild” conditions, giving rise to significant diversity in pose, scale, illumination, occlusion, and image resolution. PMC+2Directory of Open Access Journals+2

Each ear image was cropped semi-automatically from full facial images, which introduces a realistic variability — some images are very low-resolution (even less than 25×25 pixels) because of how they were extracted. PMC The dataset is structured such that there is a folder for each individual, and each person has at least 100 ear images, facilitating tasks like ear recognition, clustering, and gender classification. PMC

Several research problems can be addressed with EarVN1.0: biometric identification (ear recognition), gender recognition, detection of left vs. right ears, and super-resolution methods (since many images are low-res). PMC+1 Because of its scale and diversity, this dataset is particularly valuable for training deep-learning models under unconstrained conditions. Directory of Open Access Journals+1The dataset is openly available for academic research through Mendeley Data under a non-commercial license. Mendeley Data+1

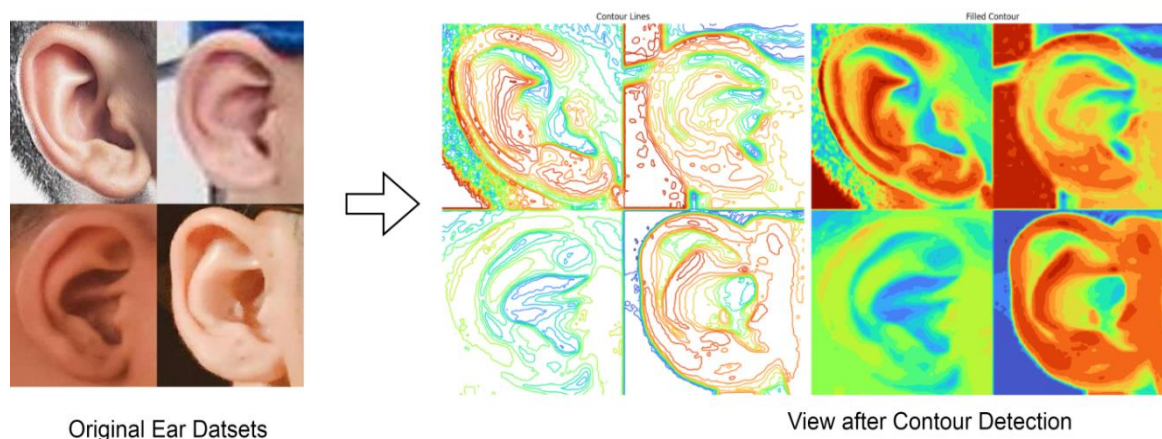


Fig. 12 application of Contour over proposed ear datasets

VI.CONCLUSION

In this project, a very successful application of using two independent biological traits, human ear and palm print, has been demonstrated. By adopting two specialized pipelines that process the data based on their own nature rather than using a general algorithm, two highly specialized processing streams have been used in this experiment. The recognition system based on the human ear was based only on the curves and edges of the ear without considering any background noise that affects the pixels based algorithm. For the hand recognition, three processes, Gabor filtering, wavelets transforms, and PCA were applied to use the frequency lines and principal ridges.

The results of empirical research demonstrate that the feature-level fusion can bring about some amazing results. In terms of performance as a unimodal technique, the two separate pipelines exhibited remarkable yet modest maximum peak accuracies of 93.3% and 91.8% in case of ear and palm, respectively. By contrast, the combination of the two different vectors of features and the application of the Mahalanobis distance metric during verification brought about impressive maximum peak accuracy of 99.9%. Thus, the combination of two biological characteristics proved to allow the elimination of their shortcomings. It is demonstrated in this study that state-of-the-art security does not necessarily demand large-scale deep learning algorithms that consume vast amounts of data. The developed framework offers a compact yet highly effective design that achieves optimal class separability. It sets out the basis on which effective security systems can be designed for environments favoring edge computing or low-resource availability.

VII.FUTURE SCOPE

However, although the multimodal method suggested by this study has proven itself accurate and reliable, there are many possible directions to continue the research and address other problems associated with security issues. First, the current study has been conducted indoors under stable lighting conditions and with high-quality imaging sensors. The next stage could be testing how the multimodal method works in an extremely difficult real-life environment, including significant fluctuations in outdoor lighting conditions or strong shadows, as well as low-resolution camera imaging.

Moreover, research must focus on the inclusion of the liveness detection process. Biometric systems, which are increasingly becoming a target of advanced methods of spoofing, such as palm images of extremely high resolution or 3D silicon-based molds of ears combined with an algorithm that determines continuous blood flow, skin elasticity, or thermal properties, will guarantee that a fake duplicate cannot fool the scanner. It will raise the level of security of the system to the banking-level standards. Another promising research direction would be the extremely optimized use of the algorithm in edge computing or minuscule devices. By optimizing further the mathematical processes involved in PCA and vectorizing the contours, the processing time can be minimized sufficiently to allow direct computation on smartphones, smartwatches, or even local IoT door locks. This prevents the need to transmit sensitive biometric data to external servers, massively increasing user privacy.

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