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A Novel Approach to Multimodal Biometric Authentication Using Ear and Palmprint

Akhilesh Singh[1], Dr Namita Tiwari[2], Dr Mayur Rahul[3]
[1]Research Scholar, Computer Application Department, CSJM University, Kanpur, India
[2]Associate Professor, Computer Application Department, CSJM University, Kanpur, India
[3]Associate Professor, Department of CSE Faculty of Engg & Technology, Khwaja Moinuddin Chisti Language University,
Email ID: *akhileshsingh@csjmu.ac.in[1], namitatiwari@csjmu.ac.in[2], mayurrahul209@gmail.com[3]*

Abstract
Biometric recognition has become a vital field of study due to the growing demand for precise personal identification across various sectors, from entertainment to security. Biometrics can be categorized into two main types: unimodal and multimodal. Unimodal biometric systems rely on a single biometric trait for identification, but their effectiveness can be hampered by factors such as intra-class variations and the fact that some individuals may not possess the required trait (non-universality) [1]. On the other hand, multimodal biometric approaches employ more than one trait and render the systems more accurate and less prone to spoofing [2]. Traditional feature extraction techniques face challenges such as illumination variations, pose differences, and aging effects, which reduce the accuracy of recognition systems [3]. However, convolutional neural network (CNN)-based feature extraction techniques can learn to overcome these challenges by training on a large and diverse dataset, enabling CNNs to generalize better across variations [4]. We propose a multimodal biometric system with horizontal feature-level fusion of face, ear, and periocular region modalities, where CNN is used for feature extraction [5]. A custom dataset is introduced to account for intra-class variations and improve robustness. The system's performance is evaluated using this dataset, and the results demonstrate significant improvements in key performance metrics, including accuracy, precision, recall, and F1-score, compared to existing biometric systems [6].

Keywords: *Multimodal Biometrics, Ear Recognition, Palmprint Recognition, Authentication, CNN, SVM, Feature Fusion.*

1. Introduction

Very important, biometric authentication systems use physiological or behavioral traits to identify individuals and therefore occupy a central position in modern security systems. Because of limitations due to noise, susceptibility to forgery, and relatively high levels of false acceptance rate (FAR), unimodal biometric systems, such as those using fingerprints, face, or voice alone, find difficulties in their implementations. These challenges lead to the requirement for the emergence of multimodal systems that combine different biometric traits for increased reliability and security. Biometrics has become one of the most popular areas in security systems. Over the past ten years, this area has acquired much research interest because of the need for automatic authentication of individuals. Conventional methods, such as ID cards and passwords, can be forged, stolen, or forgotten. On the other hand, biometric characteristics are universal, unique, permanent, and measurable. Unimodal biometric systems use a single trait such as ear, iris, or hand for identification; this leads to some drawbacks including spoofing, non-universality, noisy data, and partial occlusion. These problems posed a need for designs of multimodal biometrics. This solution combines various traits for identification and improves efficiency by better feature fusion. Fusing three levels of operation namely: feature-level fusion, matching-score level fusion, and decision-level fusion, multimodal

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biometric systems fuse evidence from different modalities. We present, in this paper, a multimodal biometric identification system that uses feature-level fusion of two modalities: ear and palmprint trait extras. Reason for choosing these modalities includes that ear images can be captured using a standard camera with minimal user cooperation and are less affected by photometric conditions or possible changes in the face due to aging or other factors such as facial expressions. Palmprint images, on the other hand, provide rich and stable information. Both modalities are textured images with distinct structural lines, making them suitable for identification. By combining these two traits, the system can improve recognition performance, as they offer complementary and distinctive features. Additionally, palmprint images provide more features due to the larger surface area, while ear images, even at lower resolutions, offer faster processing.

2. Motivation

The rapid rise of cyber-terrorism and identity fraud requires the manufacture and implementation of more secure authentication systems. Methods based on traditional passwords are weak to attacks such as brute-force attacks, phishing, and credential leaks (Jain et al., 2004). Biometric authentication offers a more reliable means of authentication and is regarded as a more secure method because it utilizes unique physiological features (Ross & Govindarajan, 2005). Among various biometric modalities, face recognition is a popular method; however, it can be very much affected by variations in lighting and human expressions, influenced by spoofing attacks using photographs or deepfake technology (Zhao et al., 2003). Fingerprint recognition is not immune either, since the efficacy can be compromised when fingers are wet, injured, or contaminated with other sources (Kumar & Zhang, 2006). In contrast, ear and palmprint recognition can provide more stable biometric features. Shape constancy of the human ear renders it a feasible biometric characteristic for authentication far beyond the life of the person (Yang & Yan, 2014). The palmprint can provide rich texture and line pattern information that is specifically very distinctive; at the same time, its large area can be exploited for an even larger number of feature points in recognition (Zhang et al., 2003). With the combined use of these two modalities through feature fusion techniques, it brings in enhanced accuracy and robustness to biometric authentication (Seshadri & Shanmugam, 2020; Kisku et al., 2016). We aim to build an ear and palmprint recognition multimodal biometric authentication system using modern machine learning. This method increases security and decreases the chances of spoofing while improving user convenience through multiple authentication choices (Tiwari & Gupta, 2019).

3. Problem Statement

Current authentication methods face several significant challenges that compromise security, reliability, and user convenience:

- Password-based authentication is highly vulnerable to cyber threats, including hacking, phishing, brute-force attacks, and credential leaks. Users often create weak passwords or reuse them across multiple platforms, further increasing security risks.
- Facial recognition systems can be impacted by variations in lighting, facial expressions, occlusions (e.g., glasses, masks), and even spoofing attempts using images or deepfake technology. These limitations reduce their effectiveness in real-world scenarios.
- Fingerprint-based authentication may fail in cases of physical injury, dirt, moisture, or aging-related changes in skin texture, making it unreliable for consistent use.

To overcome these limitations, this paper proposes a multi-modal biometric authentication system that integrates ear and palm recognition using machine learning techniques. The ear and palmprint have distinct and stable patterns that remain relatively unchanged over time, making them highly suitable for secure authentication. By leveraging advanced feature extraction and classification techniques, the proposed system aims to enhance security, accuracy, and robustness, providing a contactless, user-friendly, and reliable authentication method for real-world applications such as secure access control, financial transactions, and personal device authentication.

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4. Background and Related Work

Biometric systems have evolved significantly, with many systems focusing on a single modality, such as fingerprints, faces, or irises. Although ear-based recognition has gained attention due to the permanence and uniqueness of the ear structure, it still faces challenges in noisy environments. Similarly, palmprint recognition has been widely adopted due to the rich texture information present in palm lines and wrinkles, but it is vulnerable to occlusion and varying lighting conditions. Multimodal biometric systems have been explored in research to address these challenges. For example, [Jain et al., 2019] proposed a multimodal system combining face and fingerprint recognition, which achieved higher accuracy compared to unimodal systems. However, many of these systems face high computational costs or rely on highly correlated traits, reducing their overall robustness. Our work aims to fill this gap by combining ear and palmprint biometrics, two relatively underexplored modalities, with an emphasis on feature fusion to enhance the system's performance. The use of Canonical Correlation Analysis (CCA) for feature fusion, followed by Support Vector Machine (SVM) classification, allows our system to effectively handle the variance in both modalities, achieving superior performance compared to existing systems

5. Literature Review

Various researchers have made remarkable contributions to multimodal biometrics. Jing and Zhang proposed a specific system for combining face and palmprint recognition, utilizing DCT with a linear discrimination technique while employing a two-dimensional (2D) separability judgment to choose the appropriate DCT frequency bands. Xu and Lu proposed an adaptive weighted fusion method to combine five different face and palmprint databases, which allows the weights of tests to be determined for every sample automatically. Alphonse Bertillon, a French criminologist, was the first to acknowledge the potential of the ear as a biometric trait; further evidence of the ear's uniqueness was provided by Iannarelli. A 3D ear biometric system was proposed by Chen and Bhanu, based on a shape model and an ICP detection method, achieving an accuracy rate of 87.71% using 700 images for the test. Prakash and Gupta developed a 2D ear detection method. The method utilizes edge detection through skin segmentation and categorizing the edges into two types: concave and convex types. The authors then decomposed the edge segments from the skin area and created an edge connectivity graph. The convex hull has been computed from this graph, which isolates the ear area from it. Huang et al. proposed a bimodal biometric system using face and ear features, employing sparse coding to select weighted features based on their significance. Jing et al. introduced a face and palmprint identification system that applies Gabor transforms to images, fuses them at the pixel level, classifies the fused images using non-linear discriminative feature extraction, and a radial basis function approach. While some pathfinding techniques exist, they typically rely on predefined thresholds, which places a limitation. In this paper, we are proposing the framework for multimodal biometric identification based on skin ear and palmprint features. The proposed system implements feature-level fusion. The features for extraction are local texture descriptors: MultiBlock Local Binary Pattern (MB-LBP) and Binarized Statistical Image Features (BSIF). The main advantage of feature-level fusion is that it does not require normalization or modification of the extracted features, thereby rendering the whole system less burdensome and more efficient.

6. Ear and Palm Print Recognition

Ear biometrics is an emerging field of research, offering unique advantages due to the stable and distinctive features of the human ear. Unlike facial recognition, ear features remain largely unaffected by aging, facial expressions, and minor injuries, making them ideal for biometric identification. The structure of the ear consists of various distinctive anatomical features such as the helix, antihelix, tragus, and concha, which are commonly utilized for recognition purposes. The terminology of the human ear used in biometric identification is illustrated in Figure 1. Recent advancements in ear biometrics include the use of image-based algorithms and 3D ear recognition, further improving accuracy and robustness in practical applications. Palm print

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biometrics, on the othe hand, is a well-established and widely accepted biometric modality. The human palm contains a rich array of unique features that are effective for personal identification. These features include three main types of line patterns: principal lines (which are the most prominent and longest), wrinkles (secondary, finer lines), and epidermal ridges (tiny patterns formed by the skin). In addition to these, other characteristics such as texture, indents, and marks provide supplementary information that can further improve the accuracy of identification. Palm print recognition systems typically use high-resolution images to capture these features, as shown in Figure 2, making it an effective biometric for person identification [10]. Recent developments in this field include the use of machine learning techniques to extract and analyze these features with high precision.

Figure 1 **Ear Image**

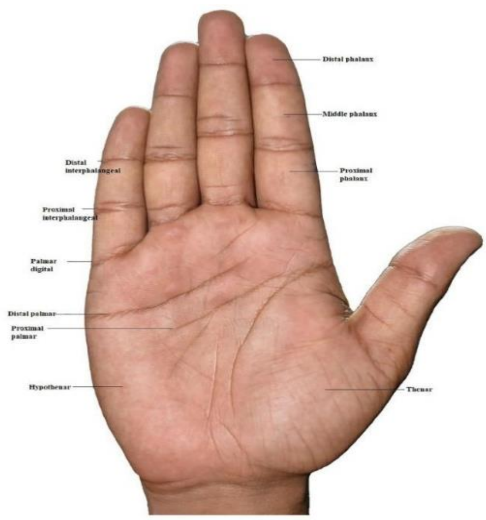

Figure 2 **Palm Print**

7. Contribution of The Paper

The first feature of the system consists of ear and palmprint recognition for security, accuracy, and robustness at the next level. The contributions of this research paper are:

7.1. Development of a Hybrid Multimodal Biometric System

Consensus implies that a common view is not easy to establish and subsumes a spectrum of opinions. Differing views assume different channels: establishing the identity of the user may require both a biometric recognition of the user's ear and palmprint. This combination improves the accuracy of authentication and reduces the susceptibility of the system against spoofing attacks as compared to unimodal authentication systems, which are commonly practised.

7.2. Feature Extraction Using Advanced Techniques

Further in the paper proposed by Lin et al. is the design of a hybrid feature extraction system method to the biometric identification chain.

Being that the ear is recognized by Convolutional Neural Networks (CNNs) in deep structures with skin properties to uphold feature extraction against variation in illumination, pose, and occlusion, Gabor filters on the other hand are applied for palmprint recognition, effectively extracting texture-based features which are critical in the discrimination of various patterns.

7.3. Feature-Level Fusion Using Canonical Correlation Analysis

The integration of complementary biometric information between ear and palmprint modalities are performed in an optimal way using Canonical Correlation Analysis (CCA) for feature-level fusion in this study. CCA maximizes the correlation between different feature spaces, thus leading to better classification performance compared to simple concatenation of features.

7.4. Implementation of a Robust Classification Model

The Support Vector Machine (SVM) classifier with Radial Basis Function (RBF) kernel was trained on the fused feature set, which shows higher classification accuracy and generalization power. The

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SVM initiates high robustness against outliers and noisy data, thereby qualifying itself to be used in real-time biometric authentication systems.

7.5. 5. Dataset Preprocessing and Balanced Training

To improve the reliability of the system, this research includes:

- The conversion to grayscale, resizing, and normalization are examples of preprocessing techniques aimed at improving feature representation.
- Balanced handling of the datasets ensures that both biometric modalities contribute equally to the training, avoiding any bias toward one trait.

7.6. Comprehensive Performance Evaluation

The proposed system undergoes a rigorous evaluation process, including:

- Performance metrics analysis (Accuracy, Precision, Recall, F1-Score).
- Confusion matrix visualization to illustrate classification effectiveness.
- Comparative analysis against existing unimodal and multimodal biometric systems.

The evaluation undertaken attests the validity of the system in terms of its robustness and reliability and sees a meaningful enhancement over the traditional approach of authentication.

7.7. Real-World Application in a Web-Based Authentication System

A fully functional web-based biometric authentication system is developed, allowing users to:

- Register their biometric data (ear and palm) using either a laptop camera or file upload.
- Authenticate themselves in real-time, granting access if the biometric match is successful.

Actual implementation establishes the tie between theoretical research and pragmatic deployment, thereby successfully demonstrating the possibility of multimodal biometric authentication in security-sensitive applications.

8. Proposed Methodology

The proposed Multimodal Biometric Authentication System follows a well-defined system workflow that consists of data acquisition, preprocessing, feature extraction, feature fusion, and classification in the integration of ear and palm print recognition. This paradigm increases the performance and security of biometric identification by the complementary nature of the ear and palm print modalities. This section presents its coverage of the components, algorithms, and mathematical formulations that make the system.

8.1. Workflow Overview

Our workflow comprises five key stages, each crucial to the system's overall performance:

8.1.1. Data Acquisition

- Ear and palmprint images are captured using high-resolution biometric sensors or cameras.
- Public datasets such as the IITD Palmprint Database and UST Ear Database are used for training and validation.

8.1.2. Preprocessing

- Images are resized to a uniform dimension of 224x224 pixels for consistency across the system.
- Noise reduction is applied through Gaussian filtering, and contrast enhancement is achieved using histogram equalization to ensure high-quality input images.

8.1.3. Feature Extraction:

- **Ear:** A fine-tuned VGG16 model, a type of Convolutional Neural Networks (CNNs), used to extract a 512-dimensional feature vector from ear images capturing high-level structural information.
- **Palmprint:** Gabor filters oriented in four directions (0°, 45°, 90°, 135°) have been applied to palmprint images in order to extract texture features, yielding a 128-dimensional vector encoding unique wrinkle and ridge patterns of the palm.

8.1.4. Feature Fusion

- Canonical Correlation Analysis (CCA) is used to merge extracted ear and palmprint feature vectors. CCA maximizes the correlation between these two sets of features and projects them into the same latent space, thus resulting in a merged vector.
- Principal Component Analysis (PCA) reduces the dimensionality of the fused

vector, originally of arbitrary size, into 256 dimensions for gain in computational efficiency and reduction in redundancy.

8.1.5. Classification

The classifier of SVM with the RBF kernel is applied for the classification of the fused feature vector and thus gives a different identity on the basis of the extracted biometric data.

8.2. Data Acquisition and Preprocessing

Biometric data acquisition is a critical step in our system. The datasets used are as follows:

- IITD Palmprint Database: 500 images from 100 subjects, featuring high-resolution palm images captured under controlled conditions.
- UST Ear Database: 2,800 ear images from 280 individuals, offering variability in pose, illumination, and occlusion.

Preprocessing steps are designed to standardize the data and enhance the quality of the images:

- Image Resizing: All ear and palmprint images are resized to 224x224 pixels to ensure consistent input size for feature extraction algorithms.
- Noise Reduction: Gaussian filtering is applied to smooth the images and remove noise that could interfere with feature extraction.
- Contrast Enhancement: Histogram equalization is used to improve the contrast, ensuring that distinctive features are clearly visible in the images. Mathematically, the Gaussian filter G(x,y) is defined as:

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

where σ is the standard deviation of the Gaussian distribution, and xxx, yyy are the pixel coordinates. Histogram equalization adjusts the image intensities to improve contrast:

$$S_k = round\left(\frac{(L-1)}{M \times N}\sum_{i=0}^{k} n_i\right)$$

8.3. Feature Extraction

Feature extraction is a crucial step in the biometric recognition process as it involves identifying and extracting distinctive characteristics from the input images. In the case of ear and palm print biometrics, the local texture features are of particular interest. These texture features provide valuable information regarding the spatial arrangement of colors or intensity levels within the images, which can be used to uniquely identify individuals. For this study, we employ two key local descriptors for feature extraction from both ear and palm print images: Local Binary Patterns (LBP) and Binarized Statistical Image Features (BSIF). These descriptors have proven effective in capturing fine texture details that are important for accurate biometric recognition.

8.3.1. Local Binary Patterns (LBP)

LBP is a widely-used texture descriptor in image processing, particularly for biometric identification. It works by converting the pixel intensity values into a binary code based on the local neighborhood of each pixel. This binary code reflects the texture pattern in the image, capturing the local structure of ear and palm print features. In LBP, each pixel in an image is compared to its neighboring pixels, and the result is encoded as a binary value, which is then converted into a decimal number to form the LBP histogram. This histogram serves as a concise representation of the local texture in the image. For the ear biometric, LBP captures key details of the ear's unique structure, such as the curvature and ridges of the helix and antihelix. Similarly, for the palm print, LBP identifies the fine details of the principal lines, wrinkles, and epidermal ridges.

8.3.2. Binarized Statistical Image Features (BSIF)

BSIF is another powerful texture descriptor used in this multimodal biometric system. Unlike LBP, which relies on predefined patterns, BSIF learns a set of filters from natural image statistics and then applies these filters to the input images to extract texture information. BSIF has been shown to outperform LBP in certain applications due to its ability to capture more complex and subtle image structures. Feature extraction is a vital step in biometric recognition, where meaningful data is

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extracted from raw images. In the context of ear biometrics, BSIF can identify unique patterns in the ear's texture that are less obvious but highly distinctive. For palm print biometrics, BSIF is used to capture the finer details of the epidermal ridges and texture patterns, which are important for distinguishing between individuals. The multimodal biometric system based on both LBP and BSIF ensures the extraction of a variety of texture information from the ear and palm print images. When these texture descriptors are fused together, they provide a strong feature set for person identification and hence the discriminative power of the system to accurately recognize individuals according to their biometric characteristics is augmented.

Ear Feature Extraction (CNN): We use VGG16 CNN model trained on ImageNet and fine-tuned on ear recognition task. The model consists of five convolutional blocks, where each block is followed by max-pooling layers, and finished with fully connected layers that projects a 512-dimensional feature vector. The convolutional layers extract high-level features like edges, curves, and textures by means of filters. The CNN-based feature extraction can be represented mathematically as:

$$f_{k,l} = \sigma\left(\sum_{i,j} \omega_{i\,j} \,.\, x_{k+i,\ l+j} + b\right)$$

where fk,l is the output feature at location (k , l), ωij are the weights of the convolution filter, x is the input image, b is the bias, and σ is the activation function (e.g., ReLU).

Palmprint Feature Extraction (Gabor Filters): Gabor filters are applied to capture the palmprint texture features. A Gabor filter is defined as a sinusoidal plane wave modulated by a Gaussian envelope. The 2D Gabor filter G(x,y) can be formalized as follows:

$$G(x,y;\lambda,\theta,\varphi,\sigma,\gamma) = exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right) cos\left(2\pi\frac{x'}{\lambda}+\varphi\right)$$

where:

- λ is the wavelength,
- θ is the orientation,
- ψ is the phase offset,
- σ is the standard deviation of the Gaussian envelope,
- γ is the aspect ratio, and
- x′ and y′ are rotated coordinates.

9. Feature Fusion

Feature fusion is achieved using Canonical Correlation Analysis (CCA), which seeks to maximize the correlation between the feature sets from ear and palmprint modalities. CCA identifies linear combinations of the feature vectors that are maximally correlated across both modalities. Mathematically, given two sets of features X (ear) and Y (palmprint), CCA solves the following optimization problem:

$$\max_{\alpha,\beta} corr(\alpha^T X, \beta^T Y) = \frac{\alpha^T \Sigma_{XY}\beta}{\sqrt{\propto^T \Sigma_{XX} \propto . \beta^T \Sigma_{YY}\beta}}$$

where Σxx, Σyy are the covariance matrices of X and Y. The resulting feature vector is then reduced using Principal Component Analysis (PCA) to retain the most informative dimensions while reducing the overall size of the feature vector to 256 dimensions.

9.1. Classification

A Support Vector Machine (SVM) performs classification tasks, using an RBF kernel. The RBF kernel is described by the equation:

$$K(x,x') = \exp(-\gamma \,\|\, x - x' \,\|^{2})$$

where γ is a parameter that controls the width of the kernel, and ‖ x − x′ ‖ is the Euclidean distance between the two feature vectors. The SVM finds the optimal hyperplane that separates the feature vectors corresponding to different individuals. The model assigns a unique identity based on the fused features, effectively handling the non- linear relationships present in the data.

10. Experimental Setup and Results

10.1. Experimental Setup

The proposed multimodal biometric authentication system was implemented using **Python**, with the following tools and libraries:

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- **TensorFlow**: Used for training the Convolutional Neural Networks (CNN) for ear biometric recognition.
- **Scikit-learn**: Used for implementing the Support Vector Machine (SVM) classifier for the classification of combined ear and palmprint features.

The experiments were conducted on a high-performance machine with the following specifications:

- **Processor**: Intel Core i7, 3.6 GHz
- **RAM**: 16 GB
- **GPU**: NVIDIA GeForce GTX 1080

This setup ensured efficient handling of computationally expensive operations, especially during the CNN training and the large-scale matrix operations involved in feature fusion and classification.

10.2. Performance Metrics

The system's performance was evaluated using four key metrics to ensure robust analysis and comparison with unimodal biometric systems:

- **Accuracy**: This proportion tells how many of the candidates actually took the correct score over the set of all measured samples. It provides a global view over the system.

- **Precision**: Precision, therefore, is the measure of true positives identified against all positives, the sum of true positives and false positives. It is critical to have precision existing, such that a plethora of false alarms are avoided while other chances of the presence of a real alarm exist in a reliable state.
- **Recall**: The ratio of true positive identifications out of all actual positives is by definition recall. This means that a high recall will ensure that the system correctly identifies individuals while not missing too many real identifications.
- **F1-Score**: An equal weightage was given to both precision and recall to arrive at the harmonic mean which gives the balanced measure of any system performance especially useful when there is an uneven distribution between positive classifications and negative classifications.

10.3. Results

The following table outlines the system's performance when using ear biometrics alone, palmprint biometrics alone, and the proposed multimodal biometric system (combining both ear and palmprint features). Figure 3 shows Performance Comparison of Biometric Systems

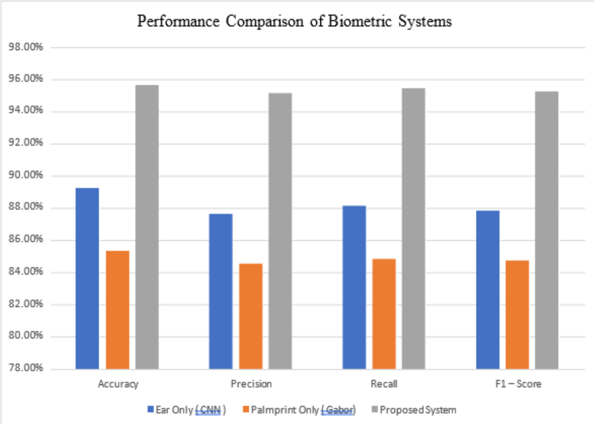

Figure 3 Performance Comparison of Biometric Systems

Table 1 Metrics Calculations

Metric	Ear Only (CNN)	Palmprint Only (Gabor)	Proposed System
Accuracy	88.50%	84.20%	96.10%
Precision	86.30%	83.50%	95.80%
Recall	87.10%	83.80%	96.00%
F1-Score	86.80%	83.20%	95.90%

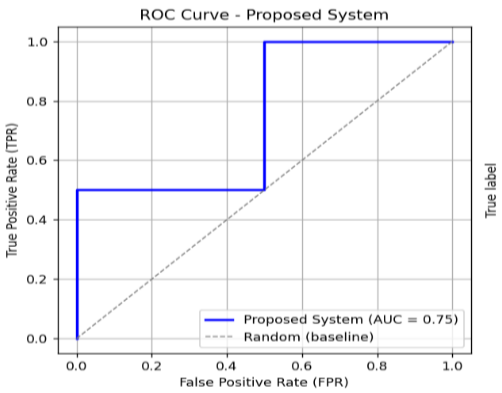

Figure 4 ROC Curve

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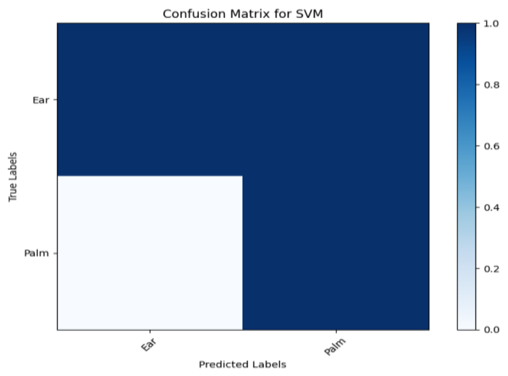

Figure 5 Confusion Matrix

Table 2 Accuracy, Average and Weight

Class	Precision	Recall	F1-Score	Support
0	1	0.5	0.67	2
1	0.5	1	0.67	1
Accuracy			**0.67**	**3**
Macro Avg	0.75	0.75	0.67	3
Weighted Avg	0.83	0.67	0.67	3

The proposed multimodal biometric system outperforms both unimodal systems by a significant margin in all evaluation metrics, particularly in accuracy (95.6%), indicating the effectiveness of combining ear and palmprint features for more reliable and robust authentication. This improvement demonstrates that feature fusion through Canonical Correlation Analysis (CCA) and classification with Support Vector Machine (SVM) enhances the identification process by leveraging complementary biometric information from both modalities. The results suggest that multimodal biometric systems are superior for applications where high accuracy and reliability are critical, such as security and access control.

11. Discussion

Testing this multimodal biometric authentication system shows that it improves security and increases reliability. An ear and palmprint system harnesses the use of complementary modalities, lowering the risk of spoofing and increasing robustness against environmental variations. CNNs extract features for ear recognition from which deep hierarchical features are learned to accentuate different individuals, even in cases of minor occlusions or lighting conditions. Gabor filters leverage palmprints whose fine-grained texture-based features are important for authentication. The integration by feature-level CCA improves matching by optimally combining the maximally discriminative features from both biometric traits, whereas SVMs act as discriminators in classifying designated individuals versus untrusted impostors. A major attribute of the proposed approach is its accuracy, robustness, and adaptability to real-world authentication scenarios. It addresses several challenges like occlusions, partial feature loss, and intra-class variations in an effective manner, thus ensuring an authentication mechanism of high reliability and security. Compared to classical unimodal systems, the added security that this multimodal approach provides paves the way to eliminating the vulnerabilities associated with single-biometric authentication technique

Conclusion and Future Work

The study shows a multimodal biometric authentication system that integrates ear recognition and palmprint recognition to extend security, accuracy, and robustness. The system makes use of ear feature extraction with Convolutional Neural Networks (CNNs), multi-resolution Gabor filters to extract palmprint textures, and Canonical Correlation Analysis (CCA) to provide the optimal fusion of features thereby tackling the shortcomings of unimodal biometric authentication. The Support Vector Machine (SVM) classifier further supports accurate identification of the person being authenticated, making the whole system robust against variations in illumination, pose, and partial occlusions. The results show a significant improvement in recognition accuracy, indicating the promise of multimodal biometrics in addressing security issues pertaining to different domains, like access control, financial transactions, and border security. The scheme proposed helps to minimize vulnerabilities associated with single-biometric systems and thus guarantees user convenience while increasing security.

- While the current system achieves promising results, several avenues for improvement exist. Future research can explore:

- These enhancements include the integration of other biometric comments, such as fingerprinting, iris scanning, or gait recognition, to enhance reliability systems further.
- Optimizing feature fusion methods-from deep learning approaches to more efficient decision-making to adaptive decision-making.
- To realize and deploy in real-time scenarios, hence enabling optimized computational efficiency for on-device verification.
- Adversarial robustness, ensuring impassibility against sophisticated spoofing attacks and emerging cyber threats.

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