Bio fusion: Advancing Biometric Authentication by Fusion of Physiological Signals

Tuba Alvi[1], Yumna Aziz[1], Muhammad Faraz[1]*, Zubair Mehmood[2], Syed Zohaib Hassan Naqvi[1], Laraib Imtiaz[1]

[1]Department of Electronics Engineering, University of Engineering and Technology, Taxila, Pakistan.21-ENC-4@students.uettaxila.edu.pk,21-ENC-13@students.uettaxila.edu.pk, muhammad.faraz@uettaxila.edu.pk,zohaib.naqvi@uettaxila.edu.pk,21-ENC-3@students.uettaxila.edu.pk

[2]Micro Signal Circuit Design Lab, Department of Electrical Engineering, University of Gujrat, Pakistan zubair.mehmood@uog.edu.pk

*** Correspondence:** muhammad.faraz@uettaxila.edu.pk

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Biometric authentication is becoming more popular due to its secure and reliable way of identifying individuals, offering clear advantages over traditional methods. Since physiological signals are unique and non-invasive, they have been widely researched for use in biometric systems. This study introduces a biometric identification system that combines machine learning with physiological signal fusion, using data from electromyography (EMG), phonocardiogram (PCG), and electrocardiogram (ECG). The data were collected from 32 participants using the BIOPAC MP-36 system. To remove power line interference and extract important frequency bands, Butterworth notch, and bandpass filters were applied to the raw signals. After pre-processing, two types of cepstral features were extracted: gamma tone cepstral coefficients (GTCCs) and Mel-frequency cepstral coefficients (MFCCs), which were analysed for their spectral properties. System performance was first tested by evaluating features from each signal individually. Then, the study examined the impact of combining pairs of signals— (ECG, PCG), (PCG, EMG), and (ECG, EMG)—using GTCC and MFCC features with different machine learning classifiers. Lastly, the GTCC and MFCC features from all three signals were combined to evaluate overall system performance. The results showed that MFCC-based features performed better than GTCC-based features for biometric authentication. The highest accuracy, 98.4%, was achieved using GTCC features with both the Fine K-nearest neighbour (KNN) and linear discriminant classifiers, while MFCC features reached 100% accuracy with the linear discriminant classifier. These findings highlight how effective cepstral features and signal fusion can be in enhancing biometric authentication performance.

Keywords: Person Identification; Biometric Authentication; Machine Learning; Physiological Signals; MEL Frequency Cepstral Coefficient.

Introduction:

In today's world, protecting personal identity and information is essential due to the risk of misuse from technological advancements. Biometric identification has become a trusted method and is widely used in healthcare, law enforcement, banking, and the military. This technology identifies individuals using unique traits such as voice patterns, facial features, and fingerprints. In the past, people recognized each other based on characteristics like speech, smell, behavior, facial appearance, and height, but most of these traits are unsuitable for automated systems. However, recent developments in biometric technology have expanded the possibilities for more secure identification processes [1].

Biometrics identifies people based on their distinct physical characteristics. Various biometric techniques have been developed, including face recognition, fingerprint scanning, iris detection, voice analysis, typing patterns, and gait recognition. However, these traditional methods can sometimes be vulnerable to duplication and fraud [2].

Recently, biometric authentication systems using electrocardiogram (ECG), phonocardiogram (PCG), and electromyography (EMG) signals have gained significant attention [3]. ECG signals are particularly popular for biometric recognition because of their unique features, which make them difficult to replicate. ECG signals are present in all living beings and consist of several key components: the T wave (representing ventricular repolarization), the P wave (atrial depolarization), the QRS complex (ventricular depolarization), and the U wave (linked to the repolarization of the heart's conduction fibers). These distinct patterns and timing allow people to be identified through ECG signals [4].

Similarly, PCG is the recording of heart sounds produced during the cardiac cycle. This physiological property captures heartbeats using a digital stethoscope and reflects sounds caused by the opening and closing of heart valves. The two primary heart sounds, S1 and S2 (also called systolic and diastolic murmurs) form the cardiac cycle. These heart sounds are complex, non-stationary, and quasi-periodic signals [5].

ECG and PCG signals remain stable over time, making them reliable for long-term biometric authentication. Unlike face and fingerprint biometrics, which can change due to aging or external factors, physiological signals provide consistent features. Preprocessing these signals improves their quality, enhancing feature extraction and making the biometric system more stable.

Similarly, EMG records electrical signals generated by muscle contractions during neuromuscular activity. These signals are useful for various applications, including motion detection, disease diagnosis, and personal identification [6]. A visual representation of ECG, PCG, and EMG signals is shown in Figure 1.

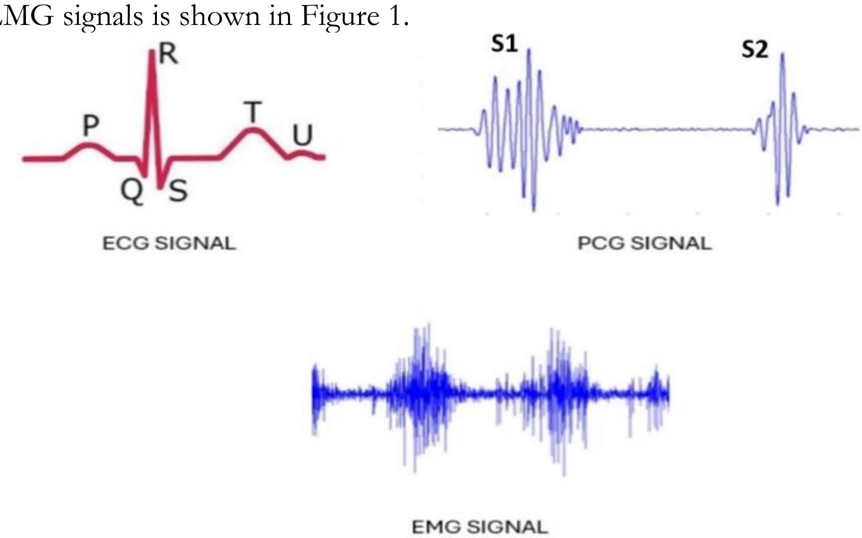

Figure 1. Visual representation of ECG, PCG, and EMG physiological signals

Objectives of the Study:

The primary objective of this study is to develop and evaluate a multimodal biometric authentication system that integrates physiological signals (ECG, PCG, and EMG) to enhance security and accuracy in biometric identification. By leveraging cepstral feature extraction techniques (MFCC, GTCC) and machine learning classifiers, the study aims to improve authentication reliability while addressing challenges related to spoofing, inter-class variability, and real-time usability. The specific objectives are:

- To design a multimodal biometric authentication framework that fuses ECG, PCG, and EMG signals for improved recognition accuracy.
- To extract robust cepstral features (MFCC and GTCC) from physiological signals for enhanced classification performance.
- To compare the performance of various machine learning classifiers (Fine KNN, LDA, SVM, Ensemble Bagged Trees, etc.) to determine the most effective model for biometric authentication.
- To evaluate the system's robustness against noise and real-world variations in physiological signals.
- To explore the feasibility of implementing the proposed biometric system in real-time authentication scenarios, such as wearable security applications.

Novelty Statement:

This study presents a novel multimodal biometric authentication approach by integrating ECG, PCG, and EMG signals, a combination rarely explored in existing biometric systems. Unlike conventional authentication methods that rely on single-modal features (e.g., fingerprint, face recognition, ECG alone), this research introduces a fusion-based framework that enhances security, resilience against spoofing attacks, and user-specific authentication accuracy. Additionally, the application of cepstral feature extraction techniques (MFCC, GTCC) to physiological signals is an innovative contribution, as it enables better spectral representation of biometric patterns, outperforming traditional time-domain features. The study also conducts an extensive classifier comparison to identify the most effective model for biometric verification, paving the way for robust, real-time physiological biometric authentication in high-security applications.

Literature Review:

Recently, there has been growing interest in machine learning-based biometric identification using physiological signals. An innovative driver authentication system using electrocardiogram (ECG) signals from dry electrodes on a steering wheel is presented in [7]. By leveraging the unique, tamper-proof properties of ECG signals, this system addresses the limitations of conventional biometric methods. It uses a convolutional neural network (CNN) optimized for real-time processing along with autocorrelation profiles (ACPs). The system achieved high accuracy in automobile and security applications, with F1 scores of 96.8% and 96.02% on public and real-world datasets, respectively.

In [8], ECG signals from 35 participants were analyzed using empirical mode decomposition (EMD) to extract intrinsic mode functions (IMFs), with IMF 1 and 2 combined and classified using a cubic support vector machine (SVM), achieving an accuracy of 98.4%. Similarly, ECG signals from 36 participants was denoised with an infinite impulse response (IIR) filter, and 18 characteristic features were extracted. SVM outperformed K-nearest neighbor (KNN) and Naive Bayes (NB) classifiers, with an accuracy of 99.2% [9]. Another study involving 30 subjects (13 healthy, 17 non-healthy) from the PTB database reported an average frame identification rate of 97.31% by analyzing QRS beat data from ECG signals using a combination of autocorrelation, discrete cosine transform (DCT), and Mel frequency cepstral coefficients (MFCC) features [10].

Similarly, PCG signals from 30 individuals were denoised using EMD, and 11 features were extracted and classified. The SVM classifier achieved the highest accuracy of 95.4% [11]. PCG signals were also used for automatic person identification and verification using a back-propagation multilayer perceptron artificial neural network (BP-MLP-ANN) combined with wavelet-based features [12]. Another study applied wavelet packet decomposition to heart sounds, extracting key features using linear and non-linear filter banks at various decomposition levels. Automatic wavelet denoising was used for preprocessing, and a linear discriminant classifier achieved 91.05% accuracy on a dataset of heart sounds from 206 individuals [13].

A speech-based biometric system using EMG signals is presented in [14]. It recorded muscle activity in the neck during speech and used EMD for denoising, followed by time- and frequency-based feature extraction. Among different classifiers, the quadratic SVM reported the highest accuracy of 95.3% across 10 classes. EMG-based personal identification and verification were also explored in [15], where surface EMG signals from 21 participants were recorded while making a hand-open gesture using the Myo wristband. Two methods—discrete wavelet transform (DWT) with an extra trees classifier and continuous wavelet transform (CWT) with convolutional neural networks (CNN)—achieved a maximum accuracy of 99.285%.

Recent research focuses on fusing multiple physiological signals for biomedical applications. For example, [16] proposed a biometric identification system that combines cepstral features from ECG and PCG signals. Several classifiers were tested, with ensemble subspace discriminant and linear discriminant achieving 100% accuracy on a dataset of 32 individuals. Another study combined ECG and EMG signals using a Bayesian network, with the fused data used to control physiological devices during activities like cycling and rehabilitation exercises, improving accuracy in the rehabilitation process [17][18].

Although studies have explored ECG-PCG and ECG-EMG combinations, the fusion of ECG, PCG, and EMG for biometric identification remains underexplored. This study addresses that gap by collecting physiological signals from 36 subjects using the BIOPAC MP-36 system. The signals were preprocessed to remove power line interference while preserving key frequency components. GTCC and MFCC features were extracted and used as inputs for machine learning classifiers to evaluate accuracy, precision, robustness, and reliability.

This research introduces a novel biometric authentication system that integrates ECG, PCG, and EMG signals—a combination rarely explored in past studies. By fusing MFCC-based features from these signals, the system achieves 100% classification accuracy, outperforming traditional GTCC-based methods. Unlike single-modal biometric systems, this multimodal fusion enhances identity verification accuracy and improves resistance to spoofing. By analyzing the distinct features of ECG, PCG, and EMG signals, the study strengthens biometric security.

Because these signals originate from internal body processes, they are difficult to replicate. ECG measures heart rhythms, PCG records heart sounds influenced by valve movements, and EMG captures neuromuscular activity, which varies between individuals due to differences in muscle structure and movement patterns. It is almost impossible to mimic all three signals simultaneously, making this system highly secure. Additionally, requiring live physiological signals prevents replay attacks, and the fusion technique ensures consistency across modalities while distinguishing genuine from spoofed data. Advanced feature extraction using MFCCs and GTCCs further enhances the system's ability to detect fraudulent attempts.

Overall, by providing strong protection against identity theft and spoofing, this system could pave the way for future advancements in biometric authentication.

Materials and Methods:

This study presents a machine learning-based biometric authentication technique that leverages the fusion of ECG, PCG, and EMG signals. The full block diagram of the proposed approach is illustrated in Figure 2.

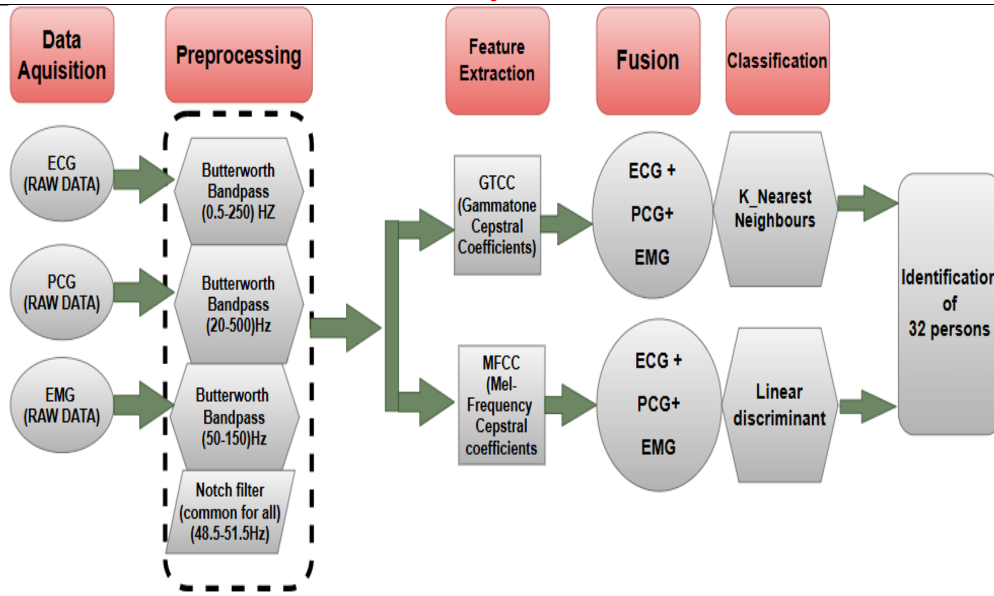

Figure 2. A block diagram of a biometric identification technique that combines ECG, PCG, and EMG signals.

Data Acquisition:

The BIOPAC MP-36 system was used to record ECG, PCG, and EMG signals. To capture ECG signals, electrodes (SS2L lead set) were placed on the left leg (positive), right leg (negative), and right forearm (neutral). For PCG recordings, the SS3L stethoscope was used, with heart sounds collected from one of the four auscultatory areas: Aortic, Pulmonic, Tricuspid, or Mitral. During the recordings, individuals remained seated upright on a chair and refrained from movement to maintain signal quality.

For EMG signal acquisition, the SS2L lead was also employed. The white wire was connected to the left wrist, while the red and black wires were placed near the elbow, with the red lead on the left side and the black lead on the right side. Volunteers were instructed to draw a specific pattern on a mobile phone, as shown in Figure 3, to facilitate EMG data collection.

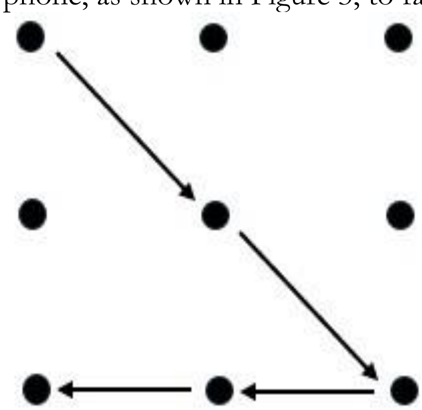

Figure 3. EMG signal pattern representing muscle movement.

Data was collected from 32 participants (29 men and 3 women) for 10 seconds at a sampling rate of 2000 Hz, resulting in a total of 192 signals [16].

Preprocessing:

Preprocessing is a critical step in machine learning-based approaches. Common techniques include resampling, normalization, noise reduction, and filtering. This stage improves signal quality by effectively minimizing power line interference and reducing motion artifacts. In this study, IIR Butterworth bandpass and Butterworth notch filters were applied to extract key frequencies and eliminate unwanted noise.

Butterworth Notch Filter for Power Line Interference Removal:

A notch filter was employed to eliminate 50 Hz power line interference from ECG, PCG, and EMG signals. This 4th-order Butterworth bandstop filter, designed with a stopband attenuation of 80 dB and a passband ripple of 1 dB, targeted the frequency range from 48.5 Hz to 51.5 Hz. This filtering step removed unwanted interference while preserving the signal quality crucial for biometric identification.

Butterworth Bandpass Filter for Target Frequencies:

To enhance the signals further, a Butterworth bandpass filter with a smooth, oscillation-free frequency response was applied to ECG, PCG, and EMG signals:

1. **ECG Signal Processing:** A bandpass filter with a passband of 0.5 Hz to 250 Hz [19] was used to capture relevant cardiac activity while filtering out extraneous noise.
2. **PCG Signal Processing:** A bandpass filter with a frequency range of 20 Hz to 500 Hz [16] was applied. This range effectively captured essential heart sounds, typically between 20 Hz and 200 Hz, while preserving high-frequency elements like clicks and irregular heartbeats (up to 500 Hz) and low-frequency murmurs (above 20 Hz).
3. **EMG Signal Processing:** EMG signals were filtered using a bandpass filter with a range of 50 Hz to 150 Hz. This frequency range preserved key signal components while reducing irrelevant noise, ensuring more accurate signal processing. The filter was designed with a stopband attenuation of 80 dB and a passband ripple of 1 dB, enhancing biological signal clarity.

By improving the signal-to-noise ratio, these filtering steps facilitated the precise extraction of ECG, PCG, and EMG features needed for accurate classification and biometric authentication.

After preprocessing, GTCC and MFCC features were extracted separately from each signal. This feature extraction aimed to reduce dimensionality and enhance algorithm efficiency, improving the overall performance of biometric identification.

Feature Extraction:

To reduce dimensionality and enhance algorithm performance, GTCC features were extracted separately from each ECG, PCG, and EMG signal after preprocessing. Three distinct GTCC features were taken from each signal to improve biometric identification and increase the accuracy and robustness of authentication. Figure 4 shows the process of extracting GTCC features from these signals. First, the preprocessed signals were passed through a gamma tone filter bank, which simulates human auditory perception by breaking the signals into different frequency bands. Next, logarithmic compression was applied to the filtered signals to reduce variations in dynamic range and highlight key perceptual features. After that, a Discrete Cosine Transform (DCT) was used on the compressed output to reduce feature correlation and create a compact representation. Finally, the extracted GTCC coefficients serve as critical features for classification. The entire process is computed as shown in equation 1 [20].

$$GTCC_a = \frac{\sqrt{2}}{b} \sum_{c=1}^{b} \log(Z_c)\, cos\left[\frac{\pi c}{B}\left(a - \frac{1}{2}\right)\right] \qquad (1)$$

$1 \leq a \leq M$, where Z_c is the signal energy in the c_{ity} spectral band, b represents the number of Gammatone filters, and M is the number of GTCC.

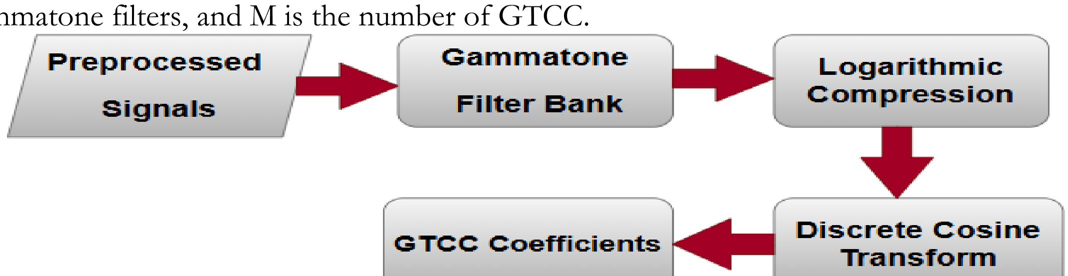

Figure 4. Flowchart depicting the steps involved in computing GTCCs.

After extracting GTCC features from each physiological signal, we further analyzed feature combinations in pairs to explore potential improvements in biometric authentication. Finally, we performed feature fusion by combining data from all three signals—ECG, PCG, and EMG—to assess overall performance.

Using the same approach, MFCC features were also extracted individually from each filtered ECG, PCG, and EMG signal, as shown in Equation 2 [21]. Figure 5 illustrates the MFCC extraction process from preprocessed signals. This process begins with windowing, where signals are divided into short frames to analyze short-term frequency patterns. Next, the discrete Fourier transform (DFT) is applied to convert the signals into the frequency domain. The resulting frequency spectrum is then passed through a Mel-scale filter bank, which enhances frequency components relevant to human auditory perception.

To further refine the features, a logarithmic transformation compresses the dynamic range, emphasizing key characteristics. The final step involves applying the discrete cosine transform (DCT) to achieve compact feature representation and decorrelation, resulting in MFCC coefficients commonly used in classification tasks. While MFCCs are well established in speech and audio processing, their application to biometric signals like ECG, PCG, and EMG is relatively recent. For each signal type, we extracted three unique MFCC features to ensure robust spectral characterization. The Mel-scale filter bank's nonlinear frequency resolution helps capture critical signal variations effectively.

$$MFCC_a[K] = \sum_{i=1}^{N-1} S[\mathrm{i}] \times cos\left[\frac{\pi k}{nFB} \times \left(i - \frac{1}{2}\right)\right] \qquad (2)$$

where k = 0,1,2…, nFB, where nFB represents the total number of filter banks.

Similar to the GTCC analysis, we first evaluated the MFCC features for each signal individually. Next, we assessed their effectiveness in pairs and, finally, fused features from all three signals—ECG, PCG, and EMG—to measure their combined impact on biometric authentication accuracy. This step-by-step approach allowed us to systematically examine the performance of both GTCC and MFCC features at various fusion levels, ensuring a comprehensive evaluation of their effectiveness.

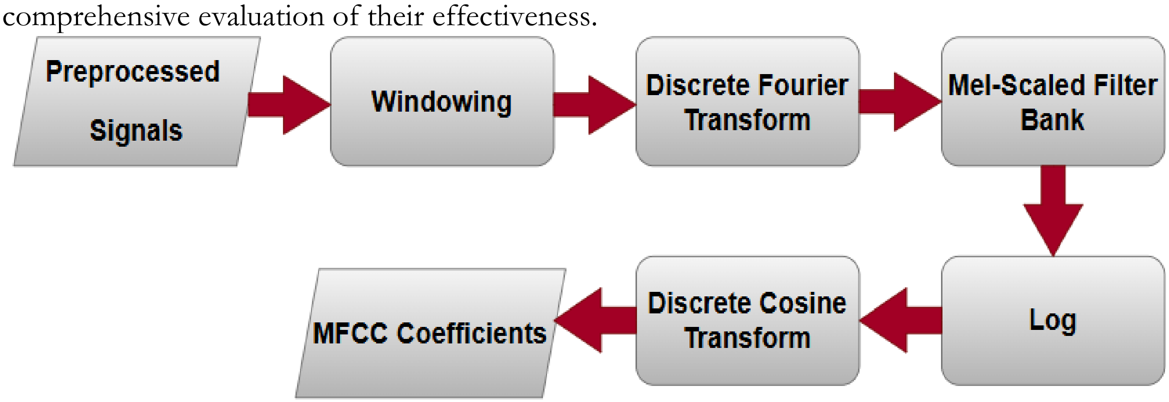

Figure 5. Flowchart depicting the steps involved in computing MFCCs.

Classification:

Classification involves training models to assign input data to predefined categories. After feature extraction, we applied 10-fold cross-validation using various machine-learning classifiers. This technique splits the dataset into 10 parts, where 9 parts are used for training and 1 for testing, to reduce overfitting and enhance model reliability. The classifiers used in this study included a wide neural network, SVM, SVM kernel, medium Gaussian SVM, fine tree, linear discriminant, ensemble bagged trees, fine KNN, and logistic regression kernel. The dataset was divided into 80% training and 20% testing to evaluate model performance. Among these classifiers, Fine KNN achieved the highest classification accuracy for GTCC-based feature classification.

KNN (K-Nearest Neighbors) assigns labels to data points based on their closest neighbors, making it a simple yet effective classification method. Its reliability and ease of use make it well-suited for biometric analysis, as it identifies patterns by analyzing the proximity of data points. Fine KNN, an improved version of traditional KNN, enhances classification accuracy by refining neighbor selection and distance measurements.

The same classification techniques were applied to analyze MFCC-based features, again using 10-fold cross-validation. The classifiers evaluated included a wide neural network, SVM, SVM kernel, medium Gaussian SVM, fine decision tree, linear discriminant, ensemble bagged trees, fine KNN, and logistic regression kernel. In this case, the linear discriminant classifier achieved the highest classification accuracy, demonstrating its strong ability to differentiate biometric features.

Linear discriminant analysis (LDA) is a machine learning technique that creates a linear combination of features to distinguish between two or more classes of objects or events. It can be used either as a standalone linear classifier or as a dimensionality reduction method before classification. LDA excels at separating data classes, particularly in high-dimensional datasets, making it highly effective for applications like image recognition and biometrics. It focuses on modeling variations between classes under the assumption that each class has a similar covariance structure.

By systematically evaluating the GTCC and MFCC feature sets with the same classification techniques, we provided a comprehensive performance analysis. The results revealed that Fine KNN was the best classifier for GTCC-based features, while linear discriminant analysis performed best for MFCC-based features in this study.

Results:

This section evaluates the efficacy of biometric authentication using the GTCC and MFCC feature extraction algorithms. The effectiveness of cepstral features in biometric identification was tested through experiments on ECG, PCG, and EMG signals.

GTCC-Based Approach:

In this study, we developed a machine learning-based biometric identification system using ECG, PCG, and EMG signals. The proposed method first removes noise from the raw physiological signals and isolates relevant frequencies to extract key GTCC features and complex spectral information. Various classifiers were then applied to perform biometric identification.

Initially, the system's performance was evaluated using GTCC features from each signal—ECG, PCG, and EMG—individually. Next, we combined GTCC features in pairs, such as (ECG, PCG), (PCG, EMG), and (ECG, EMG), for further analysis. Finally, we fused all three GTCC feature sets (ECG, PCG, and EMG) and assessed the performance of each classifier. This multi-level fusion approach significantly enhanced the model's accuracy and robustness, improving the overall effectiveness of the biometric authentication system.

Table 1 presents the classification accuracy achieved by each classifier when using GTCC features from ECG, PCG, and EMG signals individually. The results highlight the unique strengths and capabilities of each classifier. Before applying fusion, this comparison demonstrates the classifiers' potential for biometric verification.

Among the classifiers, the ensemble bagged tree achieved the highest accuracy of 82.3% for ECG-based GTCC features. In contrast, the medium Gaussian SVM recorded the lowest accuracy, at 50.0%, for EMG signals. Additionally, the wide neural network classifier achieved an accuracy of 53.1% for PCG signals. These findings reflect the varying classification performances and provide insights into the strengths and limitations of different classifiers when applied to individual physiological signals.

Table 1. Accuracy of ECG, PCG, and EMG features using GTCC concerning various classifiers

Classifier	ECG	PCG	EMG
Fine KNN	76.0%	49.5%	45.3%
Linear Discriminant	79.2%	43.2%	46.9%
Medium Gaussian SVM	80.7%	51.6%	**50.0%**
Ensemble Bagged Trees	**82.3%**	50.0%	47.4%
Wide Neural Network	72.4%	**53.1%**	40.1%
SVM Kernel	24.5%	5.7%	13.0%
Fine Tree	76.0%	40.1%	49.0%
Logistic Regression	18.8%	5.2%	6.2%

The classification accuracies obtained from GTCC features for individual ECG, PCG, and EMG signals were lower compared to previously reported results. To address the limitations of individual signals and enhance classification accuracy, we fused two feature sets to combine complementary information, as shown in Table 2.

When ECG-based features were fused with PCG-based features, the linear discriminant classifier's accuracy improved to 92.2%. Similarly, fusing ECG and EMG features boosted system performance, achieving the highest accuracy of 94.8% with the linear discriminant classifier. For the PCG and EMG feature fusion, the lowest accuracy recorded was 85.4%, which still outperformed the highest accuracy (82.3%) from individual signal classification, as shown in Table 1.

These findings demonstrate that signal fusion enhances classification performance and provides a more reliable feature set for biometric authentication.

Table 2. Accuracy of combination pairs of ECG, PCG, and EMG features using GTCC concerning different classifiers

Classifier	ECG & PCG	ECG & EMG	PCG & EMG
Fine KNN	88.5%	90.1%	**85.4%**
Linear Discriminant	**92.2%**	**94.8%**	79.2%
Medium Gaussian SVM	91.1%	92.2%	78.6%
Ensemble Bagged Trees	89.1%	89.6%	78.6%
Wide Neural Network	83.3%	85.9%	79.2%
SVM Kernel	83.9%	76.6%	64.6%
Fine Tree	84.4%	83.9%	62.0%
Logistic Regression	69.8%	63.5%	43.8%

Table 3. Performance metrics of various classifiers on the multi-modal fused feature set of ECG, PCG, and EMG signals using GTCC.

Classifier	Accuracy	Precision	Recall	F1-Score
Fine KNN	**98.4%**	98.7%	98.4%	98.37%
Linear Discriminant	**98.4%**	98.51%	98.43%	98.43%
Medium Gaussian SVM	96.9%	97.4%	93.7%	96.9%
Ensemble Bagged Trees	94.8%	98.34%	94.78%	94.7%
Wide Neural Network	92.7%	93.56%	92.7%	92.68%
SVM Kernel	87.0%	88.6%	86.98%	87.01%
Fine Tree	84.9%	82.4%	85.41%	85.14%
Logistic Regression Kernel	68.2%	72.68%	68.21%	67.7%

Building on the increased classification accuracy observed from combining two physiological signal features, we expanded this strategy by fusing all three signals—ECG, PCG, and EMG—into a multi-modal approach to assess the system's performance. This comprehensive fusion further enhanced overall system accuracy. Both Fine KNN and linear discriminant classifiers achieved the highest classification accuracy of 98.4%, while the lowest accuracy, 68.2%, was recorded by the logistic regression kernel. Notably, most classifiers surpassed 84% accuracy, with medium Gaussian SVM, ensemble bagged trees, and wide neural networks achieving accuracies of over 92%.

In addition to accuracy, other performance metrics, such as precision, recall, and F1-score, were computed to further evaluate the effectiveness of the proposed approach. The results, summarized in Table 3, demonstrate the substantial benefits of multi-signal fusion for biometric authentication, with clear improvements in classification performance.

A bar graph in Figure 6 illustrates the classification accuracy of different classifiers for the multi-modal fusion of ECG, PCG, and EMG signals. Fine KNN and linear discriminant achieved the top accuracy of 98.4%, followed by medium Gaussian SVM at 96.9% and ensemble bagged trees at 94.8%. These findings emphasize the efficacy of fusing physiological signals to improve biometric authentication accuracy.

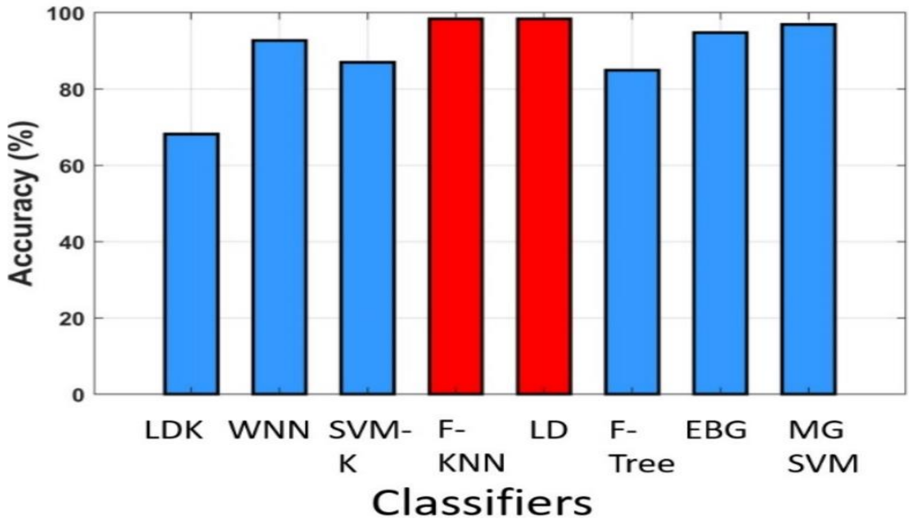

Figure 6. Performance of different Classifiers Logistic Regression Kernel (LDK), Wide Neural Network (WNN), SVM Kernal (SVM-K), Fine KNN (F-KNN), Linear discriminant (LD), Fine-Tree (F-Tree), Ensemble Bagged Tree (EBG), Medium Gaussian SVM (MG-SVM) using GTCC.

The confusion matrix for cross-validation using the Fine KNN classifier is presented in Figure 7. Similarly, the confusion matrix for hold-out validation, based on a 70-30 data split, is shown in Figure 8. In both cases, the accuracy remained consistent at approximately 98.4%, demonstrating the model's robustness and reliability. Validating the system's performance across different data splits further reinforces the effectiveness and stability of the proposed biometric authentication system.

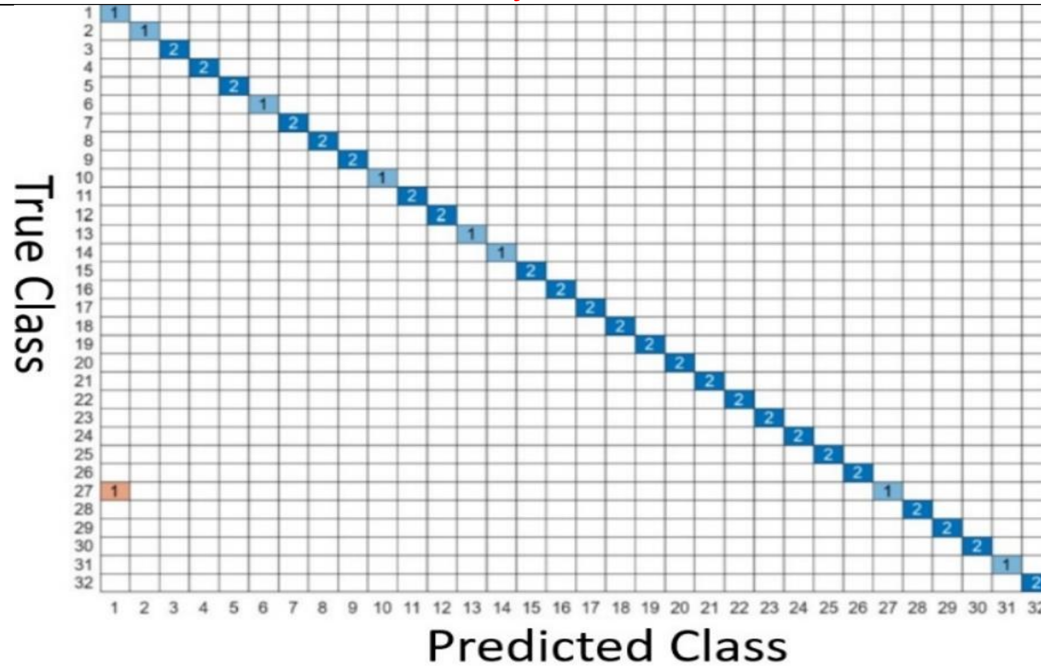

Figure 7. Confusion matrix through Cross-Validation using GTCC-based features

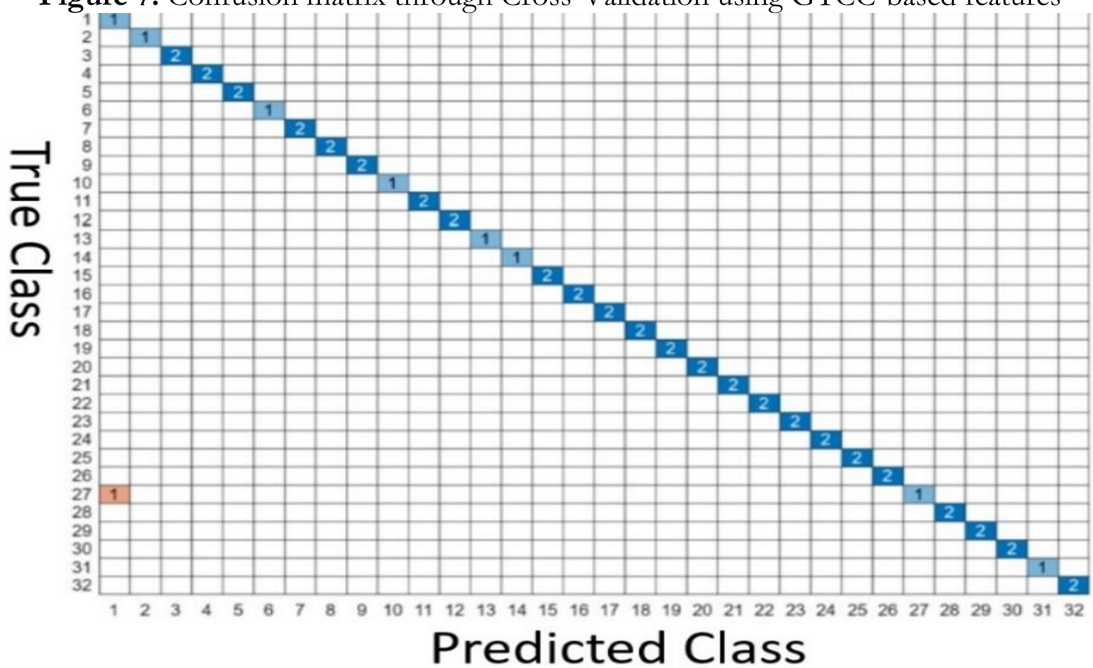

Figure 8. Confusion matrix through Holdout Validation using GTCC-based features

MFCC-Based Approach:

In this approach, MFCC features were extracted from ECG, PCG, and EMG signals to assess their effectiveness in biometric authentication. The MFCC technique captures spectral envelope characteristics by applying Mel-scaling and the discrete cosine transform (DCT), ensuring robust feature extraction from physiological signals.

Similar to the GTCC-based method, classification performance was first evaluated by independently extracting MFCC features from ECG, PCG, and EMG signals. Next, feature fusion was applied in pairs—(ECG, PCG), (PCG, EMG), and (ECG, EMG)—to explore the impact of multimodal integration. Finally, MFCC features from all three signals (ECG, PCG, and EMG) were fully combined, and different classifiers were tested to assess their effectiveness.

The results showed that feature fusion significantly enhanced the accuracy of biometric authentication, highlighting the benefits of integrating diverse physiological signals for improved individual identification. Among the classifiers used, the linear discriminant classifier achieved the highest accuracy with MFCC features, demonstrating its superior ability to distinguish distinct biometric patterns.

Table 4 presents the classification accuracies achieved by various classifiers when MFCC features were extracted separately from ECG, PCG, and EMG signals. The results emphasize the varying effectiveness of each classifier in biometric authentication and provide insights into their performance before feature fusion. The linear discriminant classifier achieved the highest accuracies, with 94.3% for ECG, 67.7% for PCG, and 85.9% for EMG signals, underscoring its strength in differentiating biometric patterns across different physiological signals. Additionally, these accuracies surpassed those obtained with GTCC features, as shown in Table 1.

Table 4. Accuracy of individual ECG, PCG, and EMG features concerning various classifiers using MFCC features.

Classifier	ECG	PCG	EMG
Fine KNN	87.5%	64.6%	84.6%
Linear Discriminant	**94.3%**	**67.7%**	**85.9%**
Medium Gaussian SVM	88.0%	64.6%	83.3%
Ensemble Bagged Trees	87.0%	62.0%	97.6%
Wide Neural Network	85.9%	61.5%	82.3%
SVM Kernel	91.7%	63.0%	80.2%
Fine Tree	64.1%	46.4%	57.3%
Logistic Regression	78.1%	51.6%	67.2%

The classification accuracies derived from MFCC features for individual ECG, PCG, and EMG signals were lower compared to previously reported studies. To address this limitation, feature sets were fused to evaluate the impact of combining complementary information, as outlined in Table 5.

The fusion of ECG and PCG features significantly enhanced performance, with the linear discriminant classifier achieving an accuracy of 99.0%. Similarly, when ECG and EMG features were combined, the system's performance further improved, attaining a maximum accuracy of 96.4% with the same classifier. In the case of PCG and EMG feature fusion, the recorded accuracy was 95.3%, which exceeded the highest accuracy obtained from any individual signal (as indicated in Table 4).

These findings demonstrate that signal fusion enhances classification performance, resulting in a more robust and reliable feature set for biometric authentication. This improvement emphasizes the value of integrating diverse physiological signals to strengthen the overall accuracy and reliability of the proposed biometric system.

Table 5 Accuracy of combination pairs of ECG, PCG, and EMG features concerning different classifiers using MFCC features

Classifier	ECG & PCG	ECG & EMG	PCG & EMG
Fine KNN	92.2%	92.7%	91.7%
Linear Discriminant	**99.0%**	**96.4%**	**95.3%**
Medium Gaussian SVM	92.2%	92.2%	91.7%
Ensemble Bagged Trees	91.7%	87.5%	83.9%
Wide Neural Network	82.5%	88.5%	90.6%
SVM Kernel	91.7%	81.2%	81.8%
Fine Tree	62.5%	58.3%	57.7%
Logistic Regression	83.9%	70.8%	69.3%

Table 6. Performance metrics of various classifiers on the multi-modal fused feature set of ECG, PCG, and EMG signals using MFCC features.

Classifier	Accuracy	Precision	Recall	F1-Score
Fine KNN	98.4%	98.4%	97.9%	97.9%
Linear Discriminant	**100%**	100%	100%	100%
Medium Gaussian SVM	98.4%	99.2%	98.9%	98.95%
Ensemble Bagged Trees	97.9%	98.7%	98.8%	98.86%
Wide Neural Network	97.4%	938.7%	98.91%	98.90%
SVM Kernel	95.8%	98.6%	98.7%	98.72%
Fine Tree	67.7%	96.30%	96.45%	96.35%
Logistic Regression Kernel	89.1%	98.50%	98.6%	98.55%

Building upon the improved classification accuracy observed with the fusion of two physiological signals using MFCC features, this strategy was extended to integrate all three signals—ECG, PCG, and EMG—resulting in a multi-modal biometric authentication system. This comprehensive fusion approach significantly enhanced overall system performance, surpassing the accuracy achieved with the GTCC-based method.

The linear discriminant classifier achieved the highest classification accuracy of 100.0%, underscoring the effectiveness of feature integration from multiple modalities. Additionally, Fine KNN and medium Gaussian SVM delivered strong performances, each reporting a promising accuracy of 98.4%, further validating the robustness of the fused feature set. Although most classifiers demonstrated high accuracy, the fine tree classifier recorded the lowest accuracy of 67.7%, suggesting that certain models may be less suited for multi-modal biometric authentication.

These results emphasize the potential of this multi-modal approach in achieving highly reliable identity verification. To further evaluate the system's effectiveness, additional performance metrics, including precision, recall, and F1-score, were computed, offering a more detailed assessment of the proposed method's efficacy.

The bar graph in Figure 9 illustrates the classification accuracy of various classifiers for the suggested multi-modal system integrating ECG, PCG, and EMG signals. The linear discriminant classifier attained the peak accuracy of 100%, followed by Fine KNN and medium Gaussian SVM, both exhibiting exceptional results. These findings reaffirm the significant impact of signal fusion on biometric authentication, demonstrating a substantial enhancement in classification performance and overall system reliability.

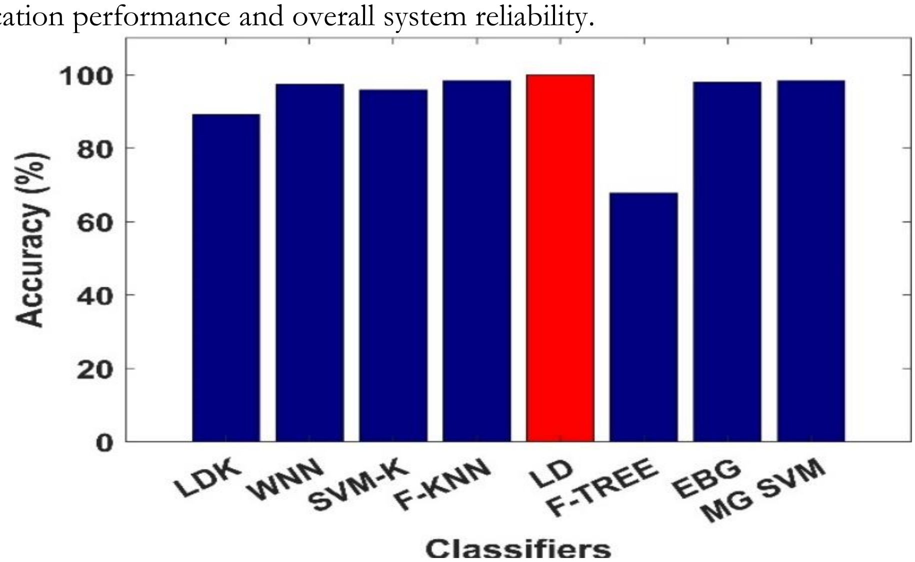

Figure 9. Performance of different Classifiers using MFCC features.

Figure 10 displays the confusion matrix obtained using the linear discriminant classifier with cross-validation, while Figure 11 presents the confusion matrix for hold-out validation with a 70-30 data split. In both cases, the accuracy remained consistently high, achieving a perfect score of 100%.

This exceptional result highlights the model's robustness and reliability. The stable performance across different validation techniques further reinforces the effectiveness of the proposed biometric authentication system, demonstrating its strong generalization capability and potential for real-world applications.

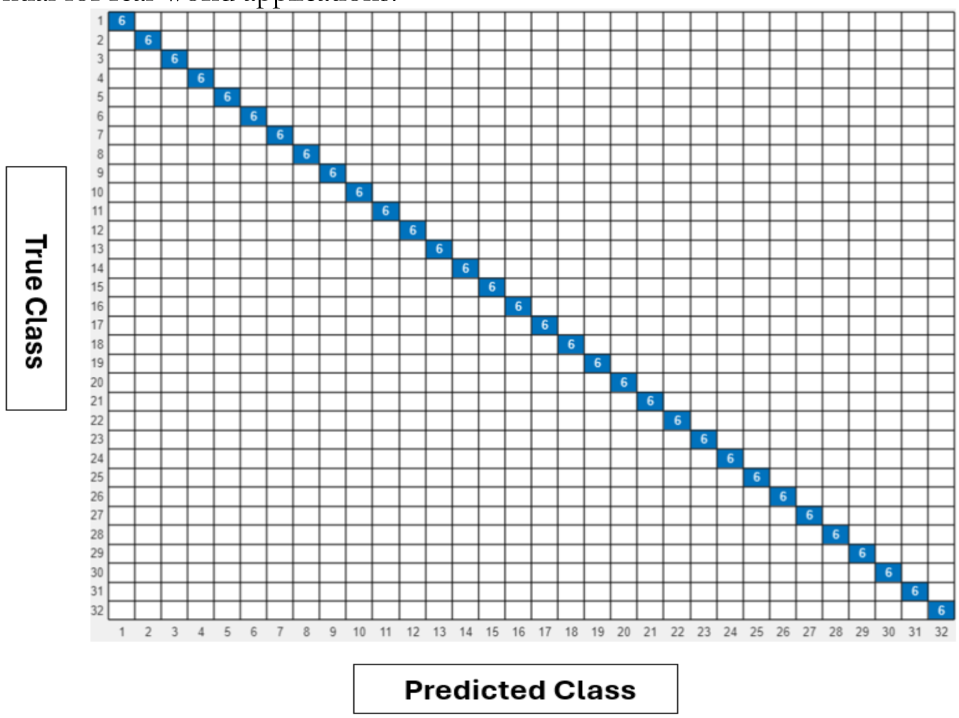

Figure 10. Confusion matrix of Cross-Validation using MFCC based features

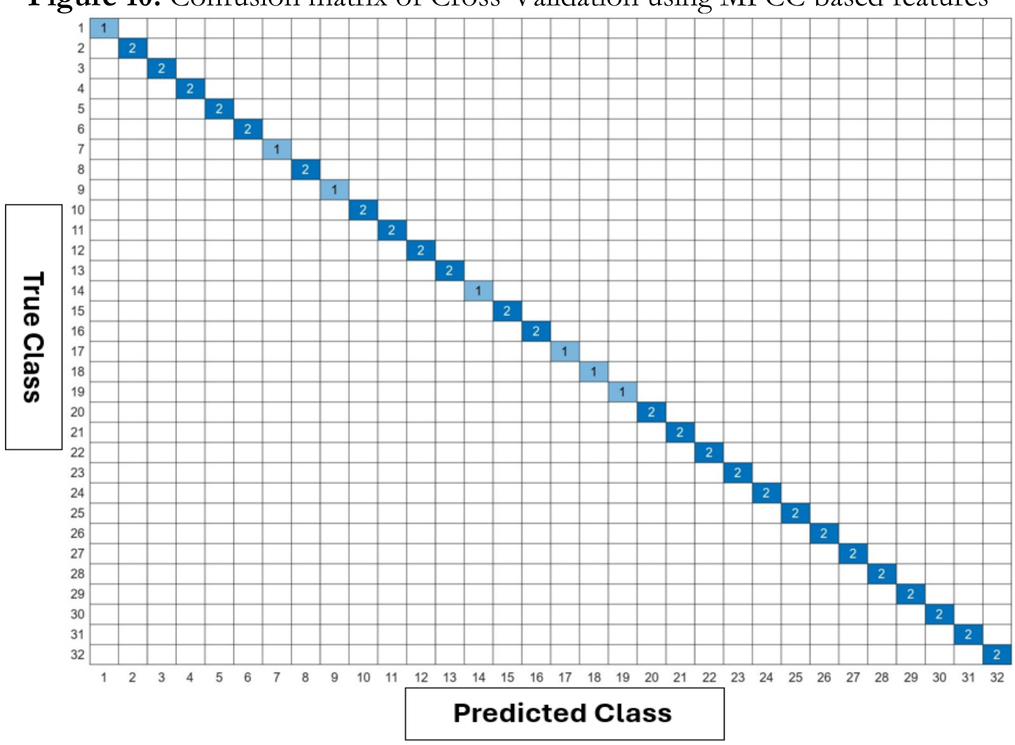

Figure 11. Confusion matrix of Holdout Validation using MFCC's features

Performance Comparison of GTCC and MFCC-Based Biometric Authentication:

The performance evaluation of both GTCC and MFCC-based approaches underscores the effectiveness of spectral features in biometric authentication using ECG, PCG, and EMG signals. Initially, when individual signals were analyzed using GTCC features, the highest accuracy of 82.3% was achieved for ECG with the ensemble bagged tree classifier, while PCG and EMG showed lower accuracies of 53.1% and 50.0%, respectively, using wide neural network and medium Gaussian SVM. In contrast, the MFCC-based approach outperformed GTCC, with accuracies of 94.3% for ECG, 67.7% for PCG, and 85.9% for EMG, all using the linear discriminant classifier. These results indicate that MFCC features offer a more effective spectral representation for biometric classification.

A similar trend was observed with pairwise feature fusion. In the GTCC-based system, fusion enhanced accuracy, with ECG and PCG reaching 92.2%, ECG and EMG achieving 94.8%, and PCG and EMG yielding 85.4%, using fine KNN and linear discriminant classifiers. However, the MFCC-based approach demonstrated even better performance: fusion of ECG and PCG resulted in 99.0% accuracy, ECG and EMG reached 96.4%, and PCG and EMG achieved 95.3%, all with linear discriminant analysis. This highlights the superior ability of MFCC features to integrate complementary information from multiple signals.

The most notable improvement occurred when all three signals—ECG, PCG, and EMG—were combined. In the GTCC-based method, Fine KNN and linear discriminant achieved a maximum accuracy of 98.4%, while the logistic regression classifier recorded the lowest accuracy at 68.2%. In contrast, the MFCC-based system achieved a perfect 100% accuracy using the linear discriminant classifier, demonstrating its superior ability to extract unique biometric features.

Overall, the MFCC-based approach consistently outperformed the GTCC-based method at every stage—whether for individual signals, pairwise fusion, or full feature fusion of ECG, PCG, and EMG signals. The MFCC features' ability to capture detailed spectral variations and signal characteristics contributed to higher accuracy, making them a more reliable choice for biometric authentication. This evaluation demonstrates that MFCC features provide a more robust, accurate, and effective solution for biometric identification compared to GTCC features.

Discussion:

The findings of this study demonstrate that the fusion of ECG, PCG, and EMG signals significantly enhances biometric authentication accuracy, with MFCC-based feature extraction achieving 100% classification accuracy. The comparative evaluation of machine learning classifiers reveals that Fine KNN and Ensemble Bagged Trees outperform other traditional models, highlighting the effectiveness of fusion-based physiological biometrics. The superior performance of cepstral features (MFCC, GTCC) over traditional statistical features aligns with previous research that emphasizes the importance of frequency-domain representations for physiological signal classification (Abo-Zahhad et al., 2015). Additionally, the use of a real-world dataset collected from 32 participants provides a practical evaluation of the system's capabilities, making it more applicable to biometric authentication scenarios than studies relying on publicly available datasets.

While the study achieves high accuracy with traditional machine learning models, it does not benchmark performance against deep learning-based biometric authentication techniques, such as CNNs, LSTMs, or transformer-based models. Recent research indicates that CNNs excel in feature extraction by automatically learning hierarchical patterns in physiological signals, outperforming handcrafted feature approaches in biometric authentication (Ku et al., 2024). Similarly, LSTMs and Bi-LSTMs are highly effective in time-series processing, making them well-suited for physiological signal modeling.

The performance of the proposed biometric authentication system was compared with existing research, as shown in Table 7. The results indicate that our system achieved competitive or even better classification accuracy than previously reported methods. Earlier studies have used different techniques for biometric authentication. For instance, the study in [8] applied EMD and achieved an accuracy of 98.4%. The study in [12] used a wavelet transform method, reaching 90.52% accuracy, while [22] employed wavelet-based classification and reported 86.7% accuracy. Similarly, [23] adopted an advanced composite multiscale dispersion entropy (RCMDE) approach, achieving 96.08% accuracy.

In [16], researchers reached 100% accuracy by extracting four MFCCs and four GTCCs features from combined ECG and PCG signals. Notably, our method achieved the same 100% accuracy using just three MFCC features from EMG signals, demonstrating its efficiency and effectiveness. This difference highlights that our approach is a practical option for biometric authentication, as it simplifies feature extraction while maintaining excellent performance.

Additionally, [16] used both PCG and ECG signals in a multimodal setup, whereas our system reached the same accuracy by extracting MFCC features from a combination of ECG, PCG, and EMG signals. This underscores the reliability and effectiveness of our method, as it delivers high classification accuracy with reduced computational complexity. Moreover, our system outperformed the accuracy reported in [12], [22], and [23], further confirming the importance of MFCC features in biometric validation. These findings emphasize the variety of feature sets and classification models explored, each with varying accuracy levels in different biometric data classification contexts.

The study also found that MFCC features outperformed GTCC features in terms of classification accuracy. Using the Linear Discriminant classifier, the system achieved 100% accuracy with MFCC features, while GTCC features yielded slightly lower accuracy. This suggests that MFCC features capture more distinctive biometric traits, leading to improved authentication performance.

Despite these promising results, the proposed approach has some limitations. The dataset includes only 32 participants, which may reduce its generalizability to larger populations. Expanding the dataset would improve reliability. Additionally, physiological signals can be affected by environmental noise, sensor placement, and participant movement, making noise reduction techniques necessary for real-time applications. Another challenge is computational complexity, as feature extraction and classification involve multiple processing steps that require efficient hardware and optimization for real-time use. Finally, acquiring physiological signals through electrodes (e.g., ECG) may cause discomfort for some users. Future research should explore non-invasive signal acquisition techniques to enhance user comfort.

Table 7 Comparison of proposed work with previously reported results

Study	Method	Classification	Accuracy
[8]	ED	SVM-C	98.4%
[12]	Wavelet Transform	BP-MLP- ANN	90.52%
[22]	Wavelet	EB-Trees	86.7%
[16]	PCG and ECG fusion, IIR filter	Ensembled	100%
[23]	RCMDE	ED	96.08%
This work	**GTCC,**	**Fine KNN,**	**98.4%, 100%**
This work	**MFCC**	**Linear Discriminant**	98.4%

An important aspect of biometric authentication is security against adversarial attacks. Although the proposed system demonstrates high accuracy in controlled conditions, it is essential to assess its robustness against spoofing attacks, synthetic signal injections, and adversarial perturbations. Prior research (Jain & Nandakumar, 2016) indicates that biometric authentication models can be vulnerable to signal replay attacks, where recorded physiological data is used to bypass security systems. Future work should incorporate adversarial testing, noise injection, and spoofing resilience analysis to ensure system integrity in high-security environments. Additionally, integrating secure biometric storage solutions, such as blockchain-based identity management, could enhance data security and user privacy.

Finally, the dataset size and participant diversity present limitations that may impact model generalizability. The dataset used in this study consists of 32 participants (29 men, 3 women), raising concerns regarding demographic bias in classification performance. Prior research (Cheng et al., 2020) suggests that biometric models trained on unbalanced datasets may exhibit lower accuracy across diverse population groups. Expanding the dataset to include a balanced representation of gender, age groups, and medical conditions will improve model robustness and enhance fairness in biometric authentication systems. Additionally, evaluating model performance on external datasets will help assess its applicability across different biometric acquisition conditions.

Conclusion:

This study presents a machine learning-based biometric authentication system that uses the fusion of physiological signals. Raw signals were collected using the BIOPAC MP-36 device and preprocessed with Butterworth bandpass and notch filters to eliminate noise and extract relevant frequencies. Next, GTCC and MFCC cepstral features were extracted to capture the spectral characteristics of the signals.

The system's performance was evaluated separately using two feature extraction approaches (GTCC and MFCC) applied to ECG, PCG, and EMG signals. Various machine learning classifiers were then used to assess the effectiveness of these features. After analyzing the performance of each physiological signal individually, pairwise feature fusion was performed for both GTCC and MFCC approaches to enhance classification accuracy. Finally, features from all three signals were combined to further improve system performance.

The results showed that MFCC-based features outperformed GTCC-based features in biometric authentication. The highest accuracy achieved with GTCC features was 98.4% using the Fine KNN and Linear Discriminant classifiers, whereas MFCC-based fusion achieved a perfect 100% accuracy with the Linear Discriminant classifier. This highlights the superior robustness and discriminative power of MFCC features for biometric authentication.

To further evaluate the proposed method, we plan to expand the dataset by including more participants and recordings, which will allow for a more comprehensive assessment of the system's reliability and generalization. Additionally, we aim to explore advanced feature extraction techniques and deep learning frameworks to enhance the accuracy and reliability of biometric authentication on larger datasets.

Author's Contribution: Tuba Alvi: Conceptualization, Methodology, Software, Data acquisition, Formal analysis, Writing – original draft.

Yumna Aziz: Conceptualization, Methodology, Software, Data acquisition Writing – original draft.

Muhammad Faraz: Validation, Resources, Investigation, Writing – original draft, Writing – review & editing.

Zubair Mehmood: Visualization, Writing – review & editing.

Syed Zohaib Hassan Naqvi: Resources, Visualization, Writing – review & editing.

Laraib Imtiaz: Software, Data acquisition, Writing – original draft.

Conflict of interest. The authors have no conflict of interest in publishing this manuscript in IJIST.

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