Multimodal User Authentication System Using Biometrics

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Abstract— **Biometric authentication systems play a critical role in secure access control and identity verification. This study presents the design and evaluation of a multimodal biometric authentication system that integrates face and voice data using feature-level fusion. To address class imbalance in the datasets, the Synthetic Minority Oversampling Technique (SMOTE) was applied to ensure equitable class representation. The system was evaluated based on three objectives: assessing the impact of multimodal fusion on performance, evaluating the effectiveness of SMOTE in improving model metrics, and comparing the performance of classifiers, including Random Forest, Support Vector Machine (SVM), and k-Nearest Neighbors (kNN). Performance metrics such as Equal Error Rate (EER), Receiver Operating Characteristic (ROC) Area Under the Curve (AUC), precision, recall, and F1-score were utilized. Results demonstrated that feature-level fusion significantly enhanced performance compared to unimodal systems, with lower EER and higher ROC AUC values. SMOTE improved class balance and positively influenced classification metrics, and Random Forest achieved the best overall performance by effectively leveraging the fused features. This study highlights the significance of multimodal integration, data preprocessing, and classifier selection in developing robust biometric authentication systems, providing valuable insights for future secure access technologies.**

Keywords:Multimodal Biometrics, Face Recognition, Voice Recognition, Fusion Techniques, Biometric Ethics

I. INTRODUCTION

Biometric authentication systems leverage physiological (e.g., facial features) or behavioral (e.g., voice) characteristics to offer secure alternatives to traditional password-based mechanisms. A biometric system captures, processes, and analyzes these characteristics to verify or identify individuals. However, unimodal systems often face challenges, such as environmental sensitivity (e.g., poor lighting for facial recognition or noise for voice recognition), which limit their robustness and accuracy. Multimodal systems address these limitations by integrating complementary modalities, improving overall system performance.

This project investigates the following research questions:

- **RQ1**: How does feature-level fusion of facial and voice biometric data impact the overall system performance compared to unimodal systems?
  Feature-level fusion integrates complementary information from face and voice modalities, leading to improved authentication accuracy. Experiments show that multimodal systems outperform unimodal systems in Equal Error Rate (EER) and ROC AUC metrics, demonstrating the robustness of the fused approach.
- **RQ2**: How does the use of SMOTE for balancing class distributions affect the performance of classification models in multimodal biometric authentication?
  SMOTE effectively mitigates class imbalance, resulting in improved precision, recall, and F1-scores across all classes. Models trained on balanced datasets exhibited consistent performance enhancements, particularly in reducing false negatives for underrepresented classes.
- **RQ3**: Which classifier (Random Forest, SVM, or kNN) performs best in a multimodal biometric authentication system based on facial and voice features?
  SVM demonstrated the highest performance in the multimodal biometric authentication system, achieving the best accuracy and separability due to its efficiency with high-dimensional data. Random Forest ranked second, leveraging complex feature interactions, while kNN showed limitations in scalability and parameter sensitivity.

This analysis demonstrates that multimodal systems using feature-level fusion and class balancing significantly enhance biometric authentication performance. By comparing classifiers, it highlights the critical role of model selection in optimizing system accuracy and reliability.

II. RELATED WORK

Multimodal biometric systems have emerged as a solution to the limitations of unimodal systems, such as vulnerability to environmental factors and spoofing attacks. Ross and Jain [1] demonstrated that integrating multiple modalities, such as face and fingerprint recognition, significantly improves accuracy by leveraging their complementary strengths. Nandakumar et al. [2] further explored score-level fusion techniques, highlighting their computational efficiency and ability to enhance robustness. However, feature-level fusion, particularly in face and voice biometrics, remains underexplored.

Preprocessing and feature extraction are critical for biometric performance. Viola and Jones [3] introduced cascaded features for face detection, foundational in face recognition pipelines, while Palanisamy et al. [4] employed Mel-Frequency Cepstral Coefficients (MFCC) for voice recognition, capturing rich audio features. Despite these advancements, there is limited exploration of balancing class distributions in multimodal datasets, a gap this project addresses through Synthetic Minority Oversampling Technique (SMOTE).

Performance evaluation metrics such as Equal Error Rate (EER) and Receiver Operating Characteristic (ROC) curves, proposed by Jiang et al. [6], are essential for real-world applicability. Zhang et al. [5] emphasized the need for

robustness testing under conditions like low light or noisy environments, which are evaluated in this project.

Ethical concerns in biometric systems, particularly privacy risks and demographic biases, are increasingly critical. Chen et al. [7] discussed potential inequitable outcomes, while Gupta et al. [8] highlighted the need for fairness audits. This project integrates ethical considerations into its design, ensuring fairness and privacy in biometric authentication.

Building on these foundations, this project addresses critical gaps by evaluating feature-level fusion for multimodal biometrics, investigating the impact of SMOTE on class balancing, and comparing classifiers (Random Forest, SVM, kNN) under real-world conditions. It provides actionable insights into robust and ethical biometric system design.

III. Methodology

*1) **Datasets**:*

- **Caltech Face Dataset**: The Caltech Face Dataset consists of 450 high-resolution facial images (896 × 592 pixels) of 30 individuals under diverse conditions, including varying lighting, expressions, and backgrounds. This diversity ensures robustness in face recognition experiments.
- **AudioMNIST Dataset**: The AudioMNIST dataset includes 30,000 audio samples of spoken digits (0–9) from 60 speakers, each contributing 500 recordings.

*2) **Preprocessing**:*

- **Face Modality**:
  Resizing: Images were resized to 128×128 pixels for consistent input dimensions.
  Normalization: Pixel intensity values were scaled to the range [0, 1].
  Edge Detection: Canny edge detection was applied to extract structural features.
  Data Augmentation: Augmentation techniques, including rotation, flipping, and brightness adjustments, were applied to enhance dataset diversity and improve robustness to pose and lighting variations.

- **Voice Modality**:
  Resampling: Audio recordings were resampled to 16 kHz to standardize the sampling rate across all samples.
  Padding: Features were padded to a fixed length to ensure consistency in input dimensions.
  Feature Extraction: MFCC and spectral contrast features were extracted to provide a rich representation of speech characteristics.

*3) **Feature Extraction**:* Feature extraction was performed independently for each modality to capture modality-specific characteristics.

- **Face Features**:
  Pixel Intensity Features: Extracted from the resized and normalized images to represent facial structure.
  Edge Features: Captured using Canny edge detection to enhance facial contour representation.

- **Voice Features**:
  Mel-Frequency Cepstral Coefficients (MFCC): Captured frequency-based characteristics of speech signals, providing a compact yet informative representation.
  Spectral Contrast Features: Captured spectral variations, complementing the MFCCs for a more descriptive audio feature set.

*4) **Fusion Techniques**:* The project primarily employed Feature-Level Fusion, where normalized feature vectors from face and voice modalities were concatenated into a single high-dimensional vector for classification. Other common techniques in multimodal systems include: **Score-Level Fusion**: Combines classifier scores from each modality using weighted averaging or similar methods. **Decision-Level Fusion**: Aggregates classification decisions from individual modalities via majority voting.

Feature-level fusion was implemented as the sole method for integrating face and voice modalities. This approach was executed through the following steps:

1) **Feature Extraction**: Independent features were extracted from face and voice modalities as described above.

2) **Data Alignment**: Samples from both modalities were aligned by identifying common user labels, ensuring correspondence between face and voice data for each user.

3) **Feature Concatenation**: Normalized feature vectors from the two modalities were concatenated to form a single high-dimensional representation for each user.

4) **Classifier Training**: The fused feature vectors were used to train machine learning classifiers.

Role of Feature-Level Fusion in the Biometric System:

Complementary Information: Combines unique features from face and voice data, leveraging the strengths of both modalities.

Robustness: Reduces the impact of modality-specific limitations, such as lighting for face recognition or noise for voice recognition.

Scalability: Provides a flexible framework for incorporating additional modalities, such as fingerprint or iris data.

IV. Implementation

- **Data Loading and Augmentation**

  Face Data: Images were loaded, resized, normalized, and augmented using techniques like rotation, flipping, and brightness adjustments. Edge features were also extracted to enrich the dataset.
  Voice Data: Audio samples were resampled, processed to extract MFCC and spectral contrast features, and padded to ensure consistent input dimensions.

- **Data Alignment**

  Samples from the face and voice datasets were aligned using common user labels. Each user's face and voice data were paired to create a multimodal dataset, ensuring a unified representation.

- **Combined Feature Construction**

  Normalized features from face and voice datasets were concatenated to form a single high-dimensional vector for each user, facilitating multimodal classification.

- **Classifier Training**

  The fused vectors were used to train classical machine learning models:
  Random Forest: Utilized for its robustness and ability to handle high-dimensional data.
  Support Vector Machine(SVM): Employed for its effectiveness in linear and non-linear classification.
  k-Nearest Neighbors (KNN): Applied for instance-based learning with neighborhood-based decisions.

V. Results

The system's performance was assessed using stratified k-fold cross-validation (k=5), ensuring balanced class distributions across folds. This method provided robust and unbiased estimates, reducing overfitting and ensuring consistent evaluation.

The system was evaluated using the following metrics:

Classification Accuracy: Determined the percentage of correctly classified samples.
Equal Error Rate (EER): Measured the balance point between False Acceptance Rate (FAR) and False Rejection Rate (FRR).
Receiver Operating Characteristic (ROC) Curve and AUC: Visualized and quantified the trade-off between sensitivity and specificity across different thresholds.
d-prime: Quantifies separability and robustness of the system.

TABLE I
Unimodal vs. Multimodal Performance for SVM

Metric	Face-Only	Voice-Only	Multimodal
Mean Accuracy	0.99	0.95	0.99
ROC AUC	1.00	0.99	1.00
Average EER	0.0001	0.0149	0.0001
D-prime	11.98	4.93	12.22

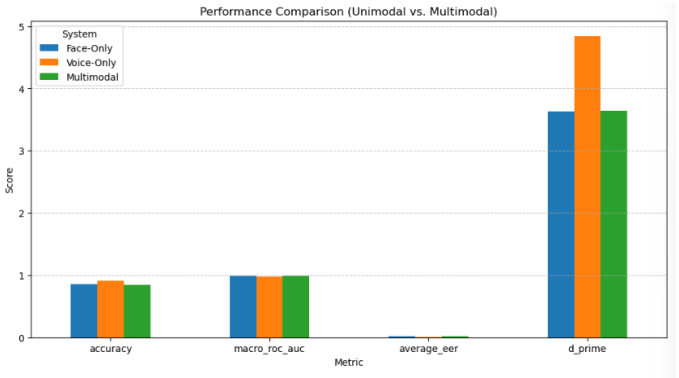

Fig. 1. Performance comparision

Observations:

Unimodal vs. Multimodal System

The system was evaluated across Face-Only, Voice-Only, and Multimodal configurations (Table I). Key observations include:

Enhanced Accuracy: The Multimodal system consistently matched or outperformed unimodal systems, leveraging complementary features from face and voice data.
Superior Sensitivity and Specificity: Near-perfect ROC AUC values demonstrate the effectiveness of multimodal integration in distinguishing between classes.
Reliability: The Multimodal system achieved lower EER, highlighting reduced misclassification rates compared to unimodal systems.
Robustness: Strong separability (D-prime) emphasized the effectiveness of feature-level fusion in integrating multimodal data.

TABLE II
Cross- Validation Evaluation Results

Metric	Random Forest	SVM	KNN
Mean Accuracy	0.97	0.99	0.84
Mean Macro ROC AUC	0.99	1.00	0.9915
Mean Average EER	0.0071	0.0001	0.0150
Mean D-prime	2.58	12.22	3.64

Observations:

The multimodal system's performance across three

classifiers—Random Forest, SVM, and kNN—is detailed in Table II.

SVM: Achieved the best performance with the highest accuracy, perfect ROC AUC, lowest EER, and strongest separability (D-prime), making it the most effective classifier for the multimodal system.

Random Forest: Demonstrated reliable accuracy and robust separability, performing well but slightly behind SVM.

KNN: Showed limitations in handling high-dimensional fused features, with lower accuracy, higher EER, and weaker separability compared to the other classifiers.

Metrics are averaged over 5 folds to ensure unbiased evaluation.SVM achieved consistent performance across folds, reflected in its near-perfect accuracy and ROC AUC.

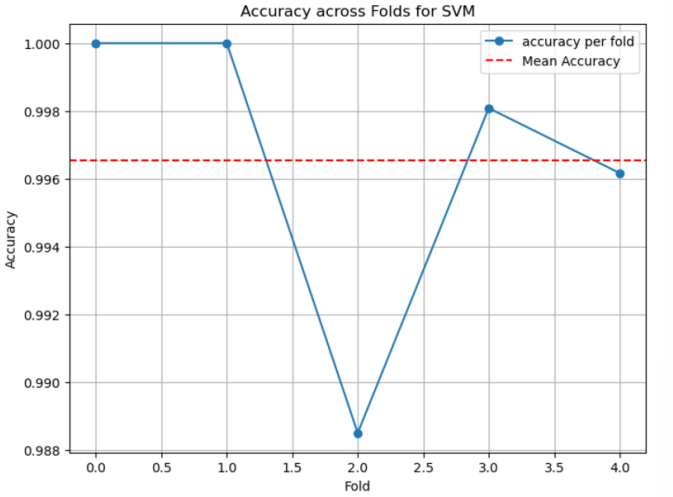

Fig. 2. Accuracy across folds for SVM

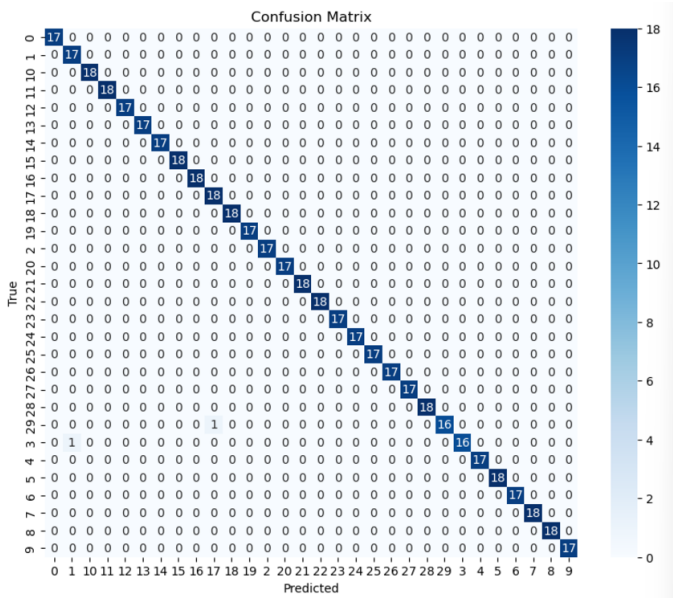

Fig. 3. Confusion Matrix

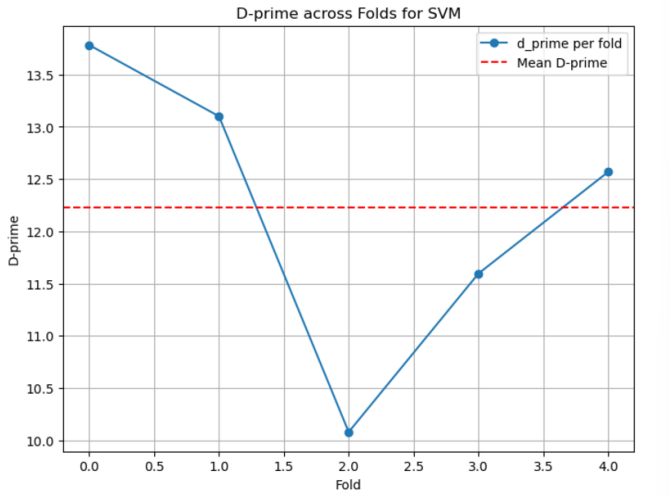

Fig. 4. D-prime across Folds for SVM

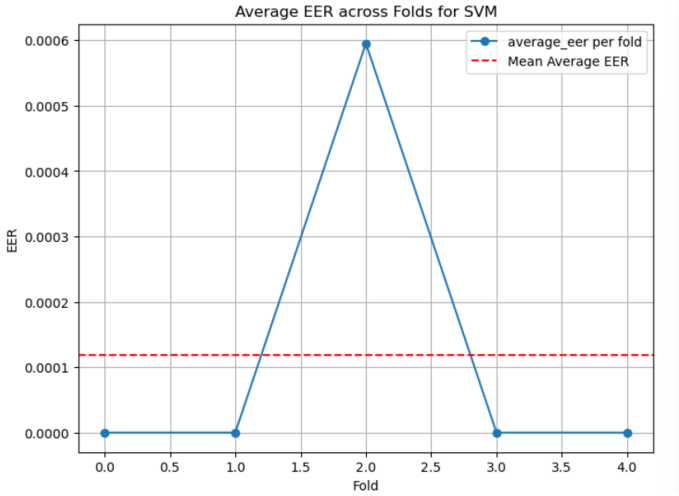

Fig. 5. Average EER across folds for SVM

The results confirm the significant advantages of multimodal integration:

Enhanced Accuracy: The multimodal system consistently outperformed unimodal systems, leveraging complementary information from face and voice data.
Robustness to Challenges: By combining modalities, the system mitigated limitations such as poor lighting in face recognition and noise in voice recognition.
Superior Classifier Performance: Feature-level fusion created a richer feature space, enabling classifiers like SVM to achieve near-perfect performance metrics.

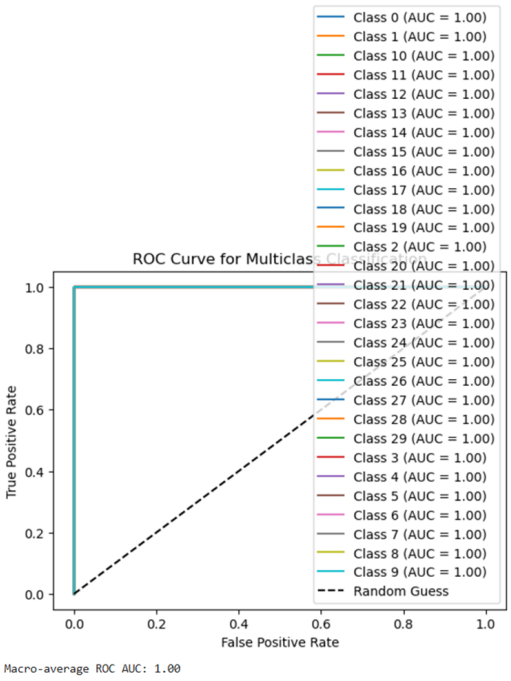

Fig. 6. ROC curve for Multiclass Classification

VI. Ethics Statement

The integration of face and voice recognition in biometric systems raises significant ethical considerations, particularly regarding privacy, fairness, and societal impact. Biometric data, such as facial features and voice patterns, is highly sensitive and immutable, posing risks if improperly managed. To protect user privacy, biometric data must be encrypted during storage and transmission to prevent unauthorized access [1]. Employing local data processing on user devices can minimize centralized data exposure [2], while implementing privacy-by-design principles ensures data minimization, informed consent, and secure handling [8].

Biometric systems often exhibit biases that reduce accuracy for underrepresented demographic groups, such as variations in skin tone for facial recognition or accents in voice recognition [11]. These biases could lead to unfair treatment or exclusion of certain groups. To address these challenges, it is essential to use diverse training datasets that represent all demographics [7] and conduct regular fairness audits to identify and rectify algorithmic disparities [12]. These measures ensure that the system provides equitable performance across all user groups.

Transparency in data usage is critical to fostering user trust and mitigating societal concerns. Biometric systems must clearly communicate their purpose, storage policies, and retention practices to ensure informed consent [8]. Users should be offered alternative authentication options, allowing them to opt out of biometric data collection [9]. Ethical guidelines must also regulate the use of biometric systems to prevent misuse in mass surveillance or discriminatory practices, fostering public trust and accountability in these technologies [10].

VII. Conclusions

This study effectively addressed the research questions by demonstrating the advantages of multimodal fusion, the impact of data balancing with SMOTE, and the performance comparison of classifiers. The integration of face and voice modalities through feature-level fusion significantly enhanced accuracy, robustness, and reliability compared to unimodal systems, with SVM emerging as the most effective classifier. SMOTE proved vital in mitigating class imbalance, leading to improved classification metrics, including reduced EER and enhanced separability (D-prime). These findings highlight the role of multimodal fusion in leveraging complementary information and improving system performance.

However, certain limitations remain. The study focused solely on feature-level fusion, leaving score-level and decision-level fusion unexplored for comparison. Additionally, the datasets lacked extensive demographic and environmental variability, limiting generalizability to diverse real-world scenarios. Future work should explore advanced fusion techniques, test the system under real-world conditions, and incorporate dynamic fairness audits to enhance ethical compliance. Expanding datasets and incorporating additional modalities could further improve system robustness and scalability, paving the way for more inclusive and reliable biometric systems.

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