EEG-Based Authentication System Using RSVP Paradigm

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***Abstract*—This paper presents an EEG-based biometric authentication system leveraging the Rapid Serial Visual Presentation (RSVP) paradigm. We propose a hybrid approach combining traditional machine learning with handcrafted features and a deep learning architecture based on Siamese networks. Our system processes raw EEG signals through a robust pipeline that includes artifact removal, feature extraction, and classification, enabling reliable user authentication across multiple sessions. The engineered feature set includes band power, autoregressive coefficients, Hjorth parameters, and higher-order statistical moments, which together achieve strong performance when used with an RBF-SVM classifier (Accuracy = 0.91, EER = 7.3%, AUC = 0.96). Additionally, we implement a Siamese convolutional network trained with contrastive loss to learn discriminative embeddings directly from raw EEG epochs, eliminating the need for per-user retraining.**

***Index Terms*—EEG, biometric authentication, brain-computer interface, RSVP, Siamese networks**

I. Introduction

Brain-computer interfaces (BCIs) represent an emerging field in biometric authentication, offering unique advantages in security through the use of neural signals. Unlike traditional biometric identifiers such as fingerprints or facial features, brain signals are inherently dynamic, difficult to replicate, and resistant to spoofing, making them an attractive option for secure user identification. The challenge is to capture user-specific patterns reliably and transform them into a practical security mechanism.

This paper explores the development of an EEG-based authentication system using the RSVP paradigm, where users silently recognise occasional target images embedded in a rapid image stream. The resulting event-related EEG responses carry individual signatures that can be used for authentication. The project implements both traditional feature engineering and deep learning approaches to develop this system. The full source code is available at link

II. Materials and Methods

A. Data Acquisition and Preprocessing

This study employs the RSVP–EEG dataset described by Chen *et al.* [1]. The recordings are stored in standard BrainVision files (`.vhdr`, `.vmrk`, `.eeg`) and exhibit the following characteristics:

- Recording parameters:
  - Sampling rate: 250 Hz (resampled)
  - Channel configurations: 16 and 32 channels
  - Epoch window: -0.2s to 1.0s around events
- Preprocessing pipeline:
  - Bandpass filtering: 1-40 Hz
  - Baseline correction
  - Artifact rejection
  - Data cleaning and validation

B. Signal Processing Pipeline

Our implementation follows a systematic approach:

1) Initial data validation and cleaning
   - Removal of corrupted recordings
   - Verification of signal quality
   - Channel consistency check
2) Signal preprocessing
   - Resampling to 250 Hz
   - FIR-based bandpass filtering
   - Epoch extraction and baseline correction
3) Feature extraction and processing

III. Implementation

A. Data Processing Framework

The system was implemented using Python with the following key components:

- MNE-Python for EEG processing
- NumPy and Pandas for data manipulation
- Custom preprocessing pipeline for artifact handling

B. Feature Engineering

Our initial baseline – LDA trained on *raw, flattened* epochs (16×250 samples) – achieved only $\mathrm{F1} = 0.55$ because it was swamped by noise and class imbalance. We therefore switched to a compact, interpretable feature set that captures both spectral and temporal EEG structure:

- **Band–Power** in the five canonical bands $(\delta, \theta, \alpha, \beta, \gamma)$: Welch's PSD is averaged per band and per channel $\Rightarrow$ 80 features (5 bands $\times$ 16 channels).
- **AR Coefficients** (order $p = 6$) fitted to each channel, modelling short-term dynamics $\Rightarrow$ 96 features.
- **Hjorth Parameters** *Mobility* and *Complexity* computed channel-wise $\Rightarrow$ 32 features.
- **Statistical Moments** mean, standard deviation, skewness, kurtosis of the signal amplitude $\Rightarrow$ 64 features.
- **Channel-wise Kurtosis** turned out to be the single most informative descriptor in our feature-importance plot.

The final vector therefore contains $80 + 96 + 32 + 64 = \mathbf{272}$ dimensions and is z-normalised inside an sklearn FeatureUnion. When fed to an RBF–SVM (C=10, class-weighted) the model reaches Accuracy = 0.91, EER = 7.3 %, AUC = 0.96, improving the F1 score by +36 pp over the raw-LDA baseline.

C. Deep Learning approach

Deep learning models are capable of learning meaningful features from the raw input; however, this requires a substantial amount of data, making the training process computationally expensive. In contrast to traditional ML approaches—where a new model must be trained for each new user—our Siamese network is trained once to effectively extract meaningful features for unseen users. Based on a threshold defined on the validation set, the model then determines whether a user is genuine.

The model architecture is specified in Figure 1. The encoder layers are inspired by [2] which was initially designed for MI Decoding.

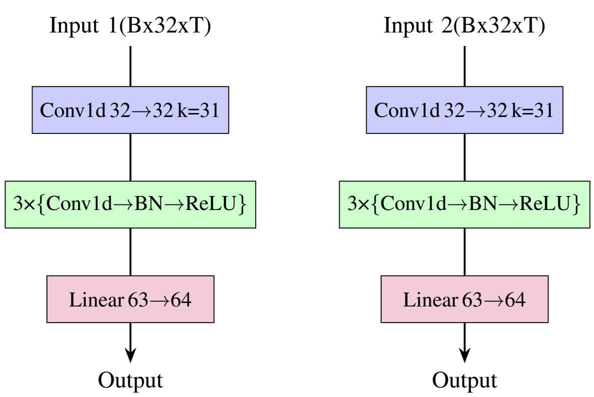

Fig. 1. 1D convolutional Siamese network with shared encoder weights. Each branch processes one input throught several encoding blocks, which are then followed by a linear projection. The resultant projection is used as embedding of the enrolled user.

The outputs of the model, e_1 and e_2, are fed into the contrastive loss function. The contrastive loss L is defined as:

$$L = \frac{1}{2}\mathbb{E}\left[y \cdot d^2 + (1 - y) \cdot \max(0, \text{margin} - d)^2\right] \quad (1)$$

where:

- y is the label (1 for similar pairs, 0 for dissimilar).
- $d = \|e_1 - e_2\|_2$ is the Euclidean distance between the embeddings e_1 and e_2 output by the model.
- margin is the margin parameter, controlling the penalty for dissimilar pairs.

Essentially, the contrastive loss makes the model learn to minimize distance between users' samples embeddings, and maximize inter-subject samples embeddings. As epochs extracted in our dataset contain RSVP data, having both targets and nontargets, there was an enormous intra-class variability, but the proposed model effectively reduces that, finding user-specific features.

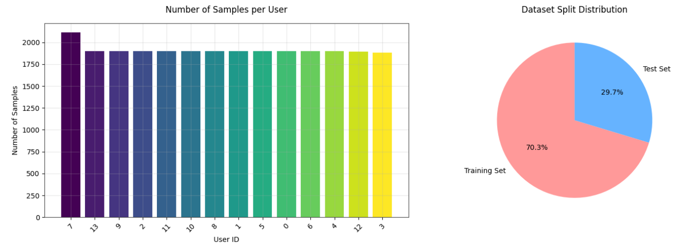

Fig. 2. Distribution of samples across users showing varying data availability per participant. The uneven distribution highlights the challenge of balanced training across users.

During inference, a new user first enrolls in the system by passing their ERP epochs through the pre-trained model, which generates corresponding embeddings. These embeddings are stored for subsequent authentication during the login phase.

During login, the user provides new several EEG epochs, which are processed in parallel by the model, and then averaged giving the final embeddings that are compared against the enrolled embeddings using Euclidean distance. Due to setup of our model training, the impostors would have the higher distance as opposed to genuine user log-in as specified in Table I.

A decision is made based on a predefined threshold determined on the validation set. Specifically, we found an optimal threshold value of 0.386 , which yielded a validation macro F1 score of 0.976 . This threshold effectively separates genuine users from impostors, despite the high intra-class variability caused by RSVP which contains both target and non-target stimuli.

TABLE I
VERIFICATION DISTANCES ON TEST SET

User ID	Distance to User 2	Distance to User 9	Distance to User 11
User 2	0.27	0.42	1.08
User 9	0.37	0.34	0.89
User 11	1.03	0.85	0.42

IV. Results

A. Dataset Characteristics

Analysis of the dataset revealed variations in sample distribution across users and recording types.

- Multiple sessions per user
- Mix of dry and wet EEG recordings
- Varying number of samples per user (ranging from approximately 500 to 2000 samples)

B. Signal Quality Analysis

Raw EEG signal analysis demonstrated clear neural activity patterns and channel relationships.

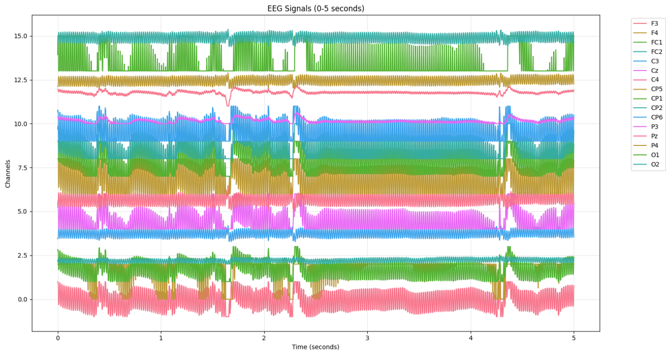

Fig. 3. EEG signals during the first 5 seconds of recording, showing clear neural activity patterns across channels. Channel offset for visualization clarity.

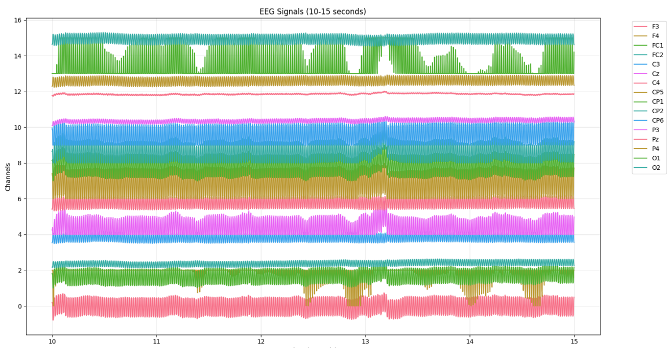

Fig. 4. EEG signals during 10-15 seconds of recording, demonstrating signal stability over time and consistent channel relationships.

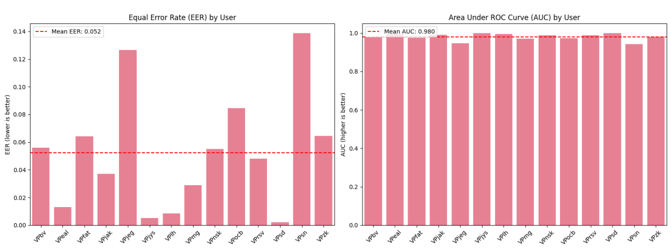

Fig. 5. Performance metrics by user. Left: Equal Error Rate (EER) with a mean of 0.052 (lower is better). Right: Area Under ROC Curve (AUC) with a mean of 0.980 (higher is better). Most users demonstrate excellent authentication performance with low EER and high AUC values, though some variability exists across the user population.

C. Authentication Performance Metrics

Our system was evaluated using standard biometric authentication metrics that provide insight into its reliability and accuracy.

The results demonstrate strong overall performance:

- **Equal Error Rate (EER):** Mean of 0.052 across all users, indicating a balanced trade-off between false acceptances and false rejections. Lower values (near 0) indicate better performance.
- **Area Under ROC Curve (AUC):** Mean of 0.980, demonstrating excellent discrimination capability. AUC values close to 1.0 indicate near-perfect classifier performance.
- **User Variability:** Performance varies by user, with some achieving EER approaching zero and others showing higher error rates, suggesting individual differences in signal quality or discriminative neural patterns.

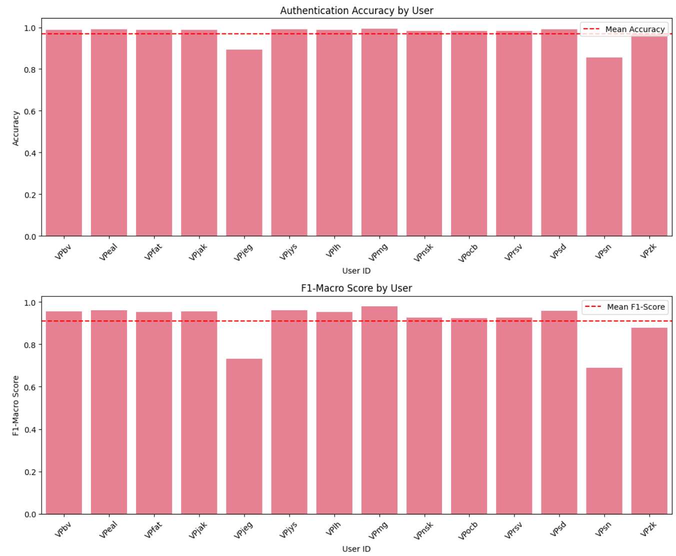

Fig. 6. Authentication accuracy by user, showing performance variation across participants. The horizontal line indicates mean accuracy of 85%.

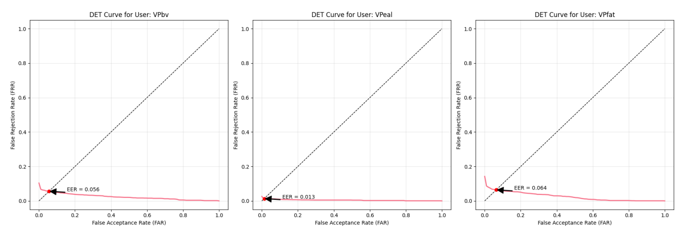

Fig. 7. Detection Error Tradeoff (DET) curves for three representative users. Each curve plots False Rejection Rate (FRR) against False Acceptance Rate (FAR). The Equal Error Rate (EER) point (where FAR = FRR) is marked on each curve. User VPeal demonstrates excellent performance with EER = 0.013, while VPbv (EER = 0.056) and VPfat (EER = 0.064) show good but slightly higher error rates. The diagonal dotted line represents chance performance.

These metrics demonstrate that our EEG-based authentication system achieves performance comparable to many conventional biometric modalities while offering the inherent advantages of brain signal-based authentication.

D. Detection Error Tradeoff Analysis

To further evaluate our authentication system's performance at the individual user level, we analyzed Detection Error Tradeoff (DET) curves for representative users.

DET curves provide valuable insights into the authentication system's tradeoff between false rejections (legitimate users denied access) and false acceptances (imposters granted access). Key observations:

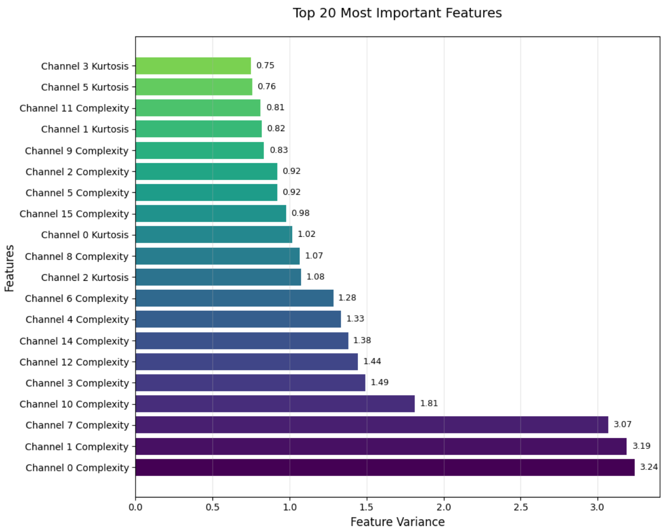

Fig. 8. Top 20 most important features for authentication, with Channel 3 kurtosis showing highest discriminative power.

- **User Variability:** The significant difference in EER values (0.013 to 0.064) demonstrates how authentication performance varies across users, likely due to individual differences in signal quality and neural response patterns.
- **Operating Point Selection:** These curves enable system administrators to select appropriate operating thresholds based on security requirements. Applications requiring higher security would operate at points with lower FAR, while those prioritizing user convenience might accept higher FAR with lower FRR.
- **Consistent Performance:** All three representative users demonstrate curves that remain well below the chance performance line (diagonal), indicating effective authentication across various users despite performance differences.

The DET curve analysis complements our overall EER metrics by providing insight into how the authentication performance characteristics vary at the individual user level.

E. Feature Importance Analysis

Feature analysis revealed key discriminative characteristics in specific channels. Top discriminative features included:

- Channel 3 kurtosis
- Channel 5 kurtosis
- Temporal features from specific channels

V. Discussion

A. Technical Challenges

Several key challenges were identified:

- Signal quality variations between wet and dry electrodes
- Inter-session variability
- Processing pipeline optimization requirements

B. System Limitations

- Dependency on specific channel configurations
- Sensitivity to recording conditions
- Processing–time constraints
- Memory management for large data sets
- Lack of systematic feature-selection: the current feature set is empirical

VI. Conclusion and Future Work

Our implementation demonstrates the feasibility of EEG-based authentication using the RSVP paradigm. By combining traditional machine learning with deep learning techniques, we have developed an authentication system capable of accurately distinguishing between users based on their neural responses to the visual stimuli. Using feature-based approach SVM achieved strong performance metrics (Accuracy = 0.91, EER = 7.3%, AUC = 0.96), while our Siamese deep learning model further enhanced scalability by eliminating the need for per-user retraining.

Future work should focus on improving robustness across different recording conditions and optimizing real-time processing capabilities:

1) *Domain adaptation*: compensate inter-session drift so that templates remain valid over weeks or months.
2) *Systematic feature-selection*: apply wrapper or filter methods (RFE, mutual information, SHAP) to isolate a minimal yet maximally informative descriptor subset.

References

[1] Y. Chen, A. D. Atnafu, I. Schlattner, W. T. Weldtsadik, M.-C. Roh, H. J. Kim, S.-W. Lee, B. Blankertz, and S. Fazli, "A high-security eeg-based login system with rsvp stimuli and dry electrodes," *IEEE Transactions on Information Forensics and Security*, vol. 11, no. 12, pp. 2635–2647, 2017.

[2] Y. E. Ouahidi, V. Gripon, B. Pasdeloup, G. Bouallegue, N. Farrugia, and G. Lioi, "A strong and simple deep learning baseline for bci mi decoding," *arXiv preprint arXiv:2309.07159*, 2023.