

Decoding Visual Categories: From EEG Signals to Cognitive State Classification

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Introduction

- Rapid human recognition of faces and gestures reflects complex neural dynamics that unfold within milliseconds.
- Machine learning and multivariate decoding methods can leverage high-dimensional EEG features to reveal subtle differences in neural responses.
- Decoding refers to the process of identifying or predicting experimental conditions, such as stimuli or participant responses, from patterns of neural activity recorded in EEG data.
- Decoding stimulus categories from EEG holds promise for advancing brain-computer interfaces and deepening our understanding of social and symbolic information processing.
- Brain-computer interfaces (BCIs) are systems that translate neural activity into commands for external devices, enabling direct communication between the brain and computers.

Research Question

- Can machine learning classifiers reliably distinguish between face and hand gesture stimuli based solely on a minimally preprocessed EEG signal?
- Can advanced models outperform the common support vector machine approach typically used in neural decoding?

Dataset

- EEG data were drawn from the public EEG recording from Soylu (2017), focusing on face and hand gesture perception.
- Stimuli comprised human faces (varied emotional expressions) and hand gestures.



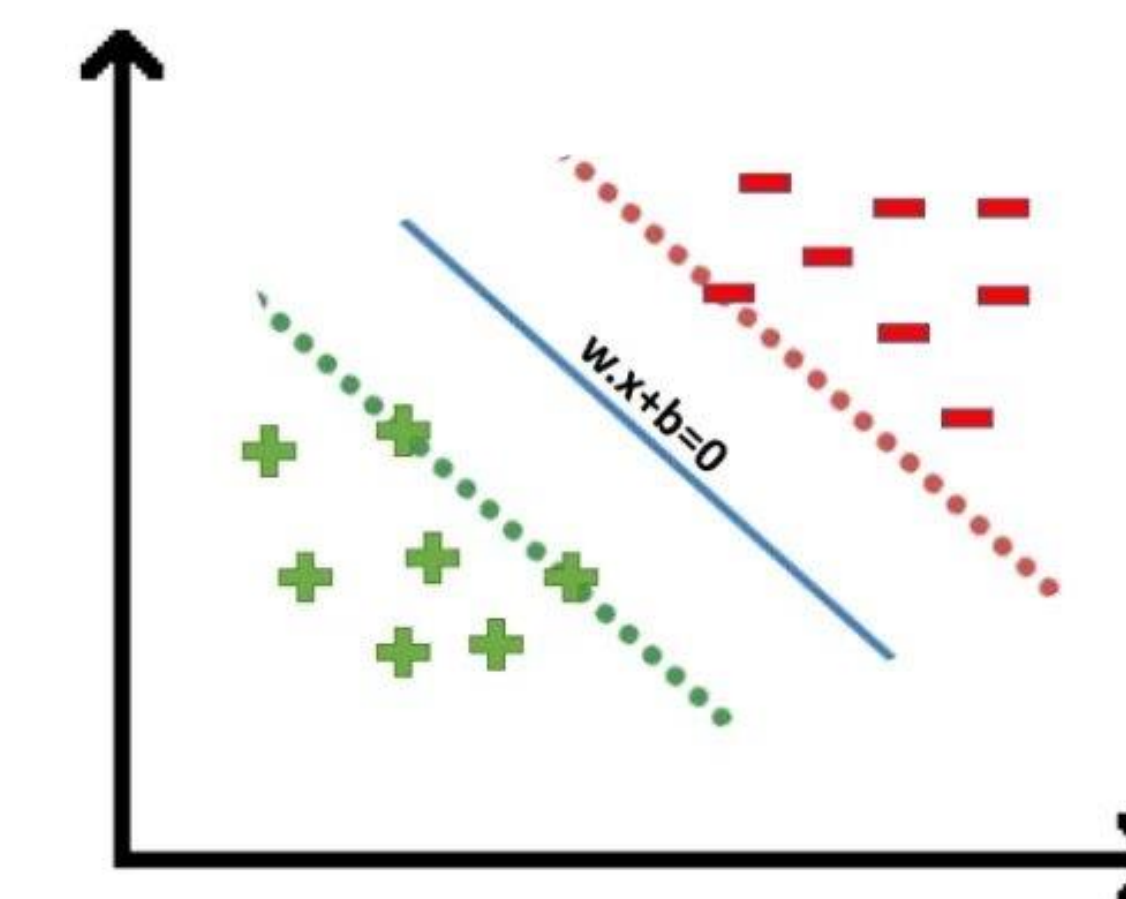
Methods

- **Preprocessing steps:** EEG data band-pass filtered (1–40 Hz), segmented into time-locked epochs around each stimulus (-200 ms to 800 ms), and cleaned of large artifacts.

- **Decoding Models:**

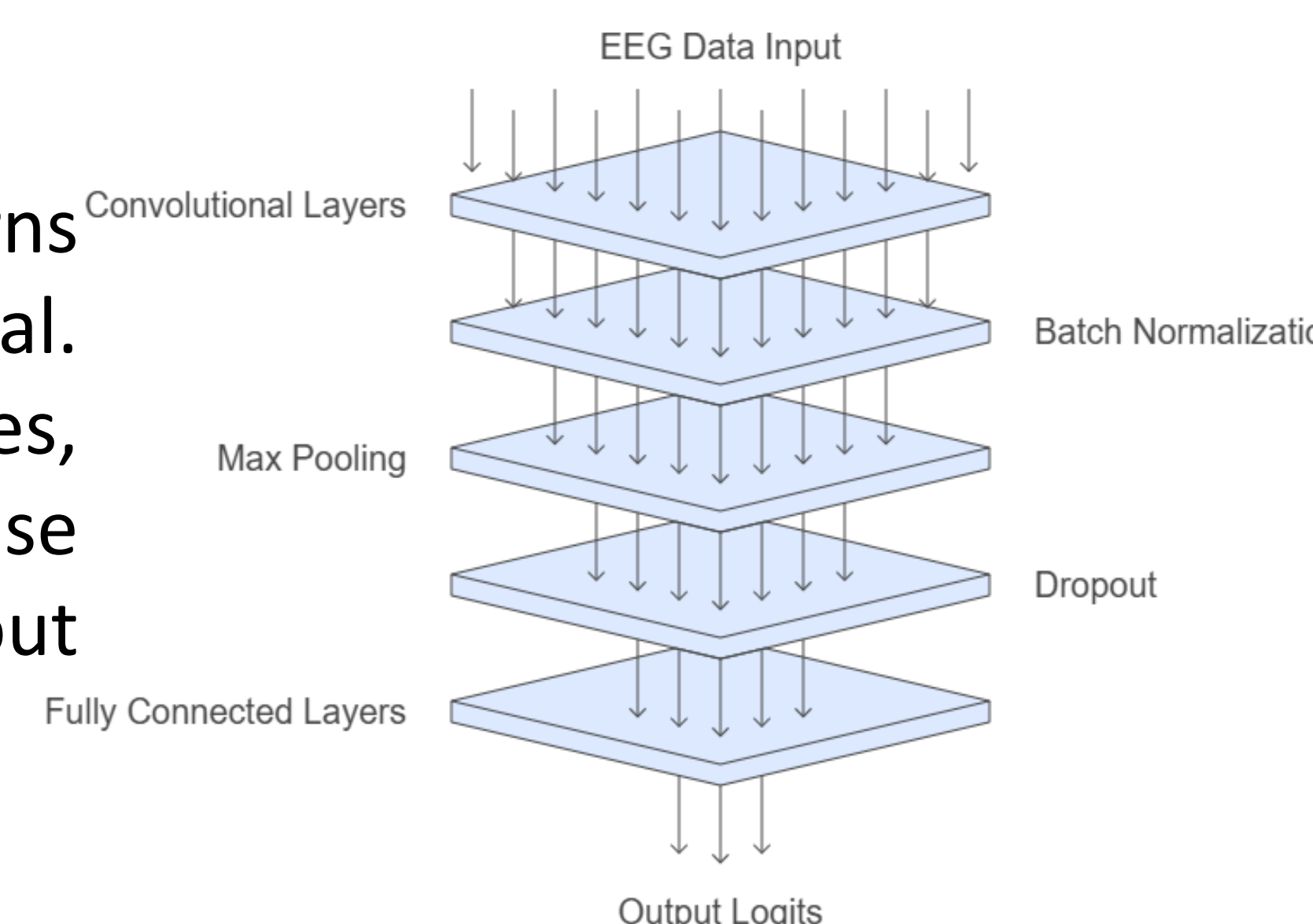
➤ Support Vector Machine Baseline:

We used a radial-basis SVM—a common, interpretable choice in neuroscience—as our baseline. Each epoch was flattened into a feature vector, standardized, and classified. This model sets a strong, familiar benchmark for decoding performance.



➤ Convolutional Neural Network (CNN):

A lightweight 1-D CNN automatically learns temporal patterns in each EEG trial. Convolutional layers extract timing features, pooling layers reduce data size, and dense layers map to class probabilities without manual feature design.

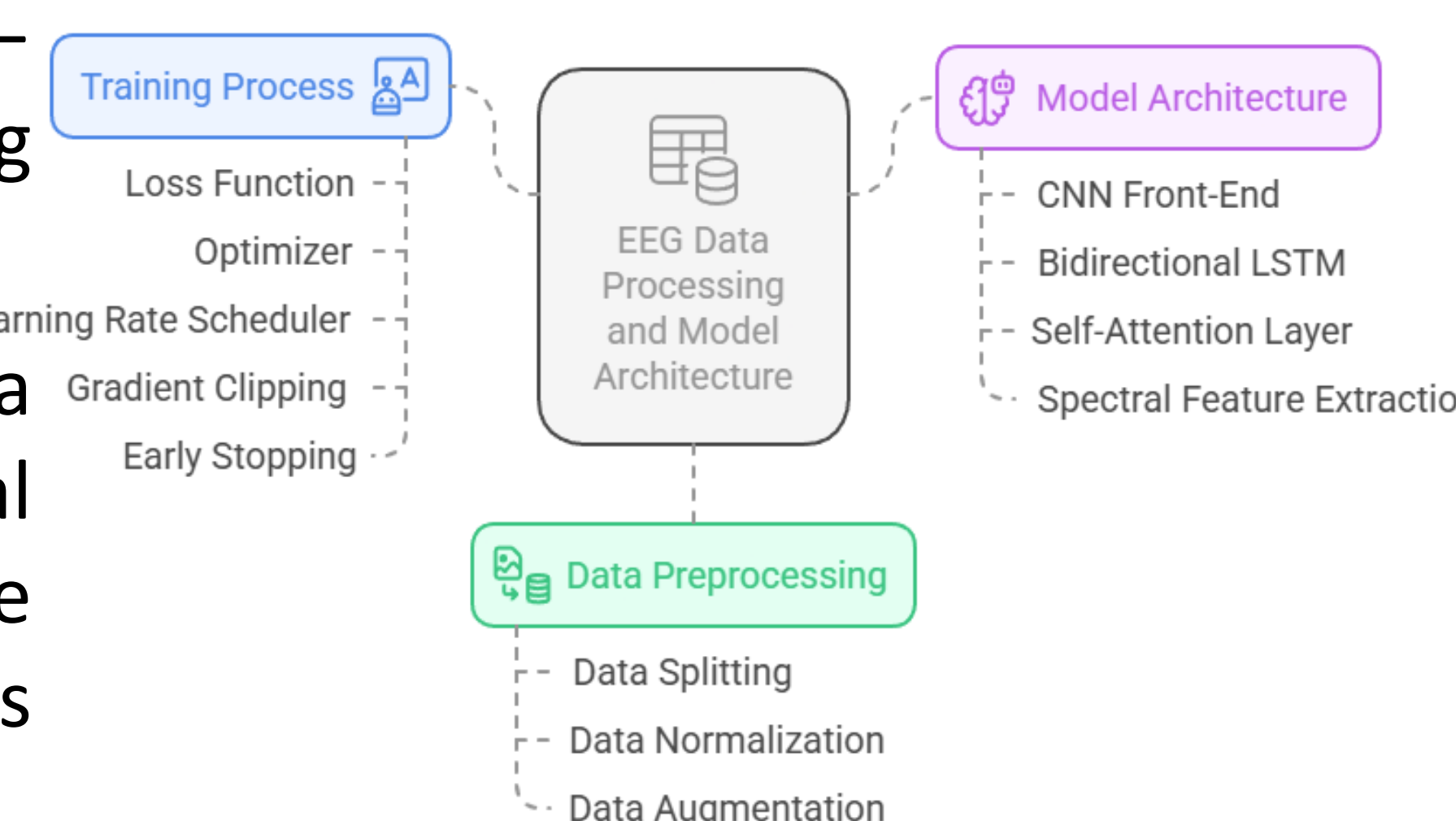


➤ Long Short-Term Memory (LSTM):

This model learn patterns across time—ideal for capturing the rhythm and timing of brain activity.

An LSTM network treats each trial as a time series, capturing sequential dependencies. Its memory gates enable modeling of dynamic EEG fluctuations over time.

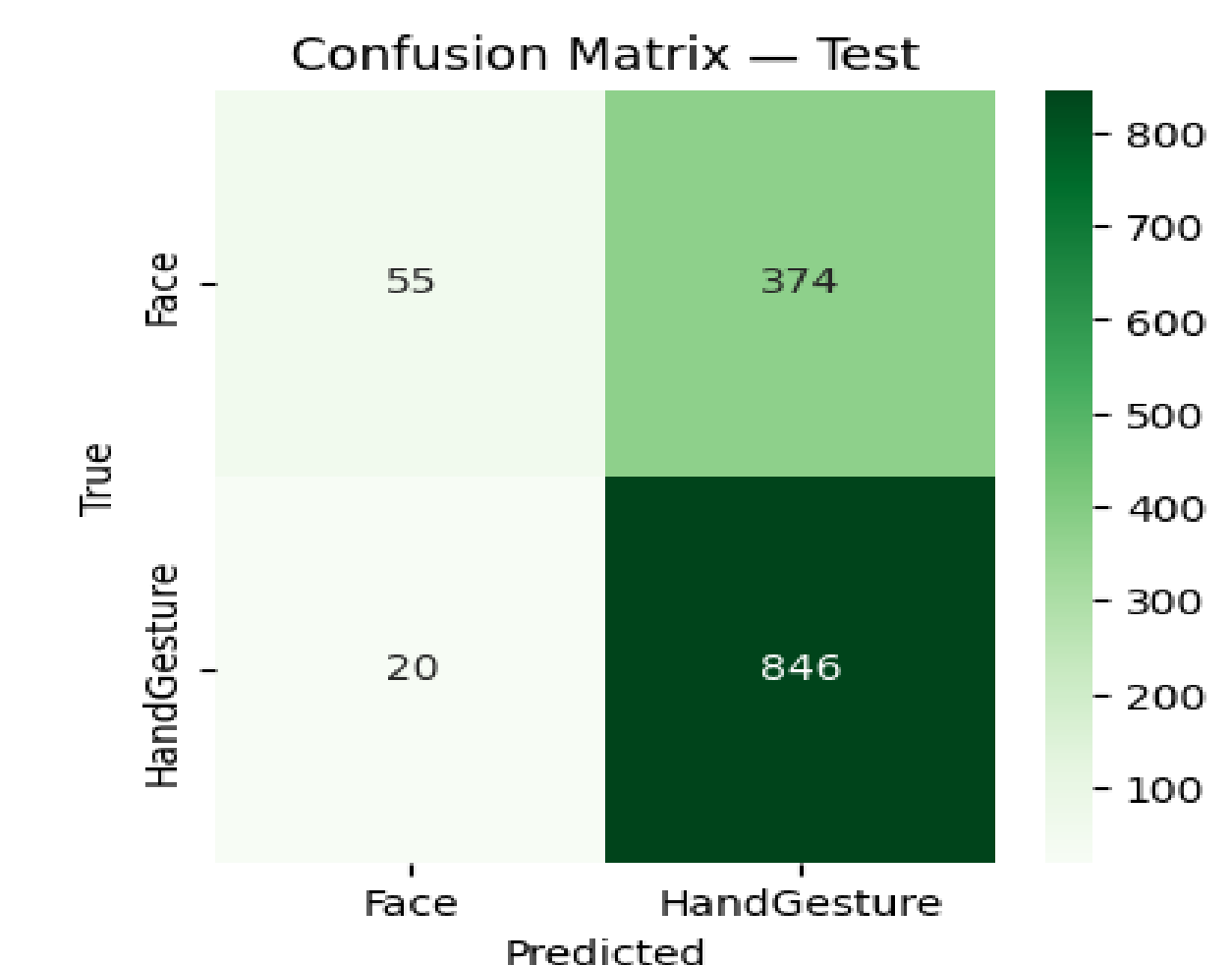
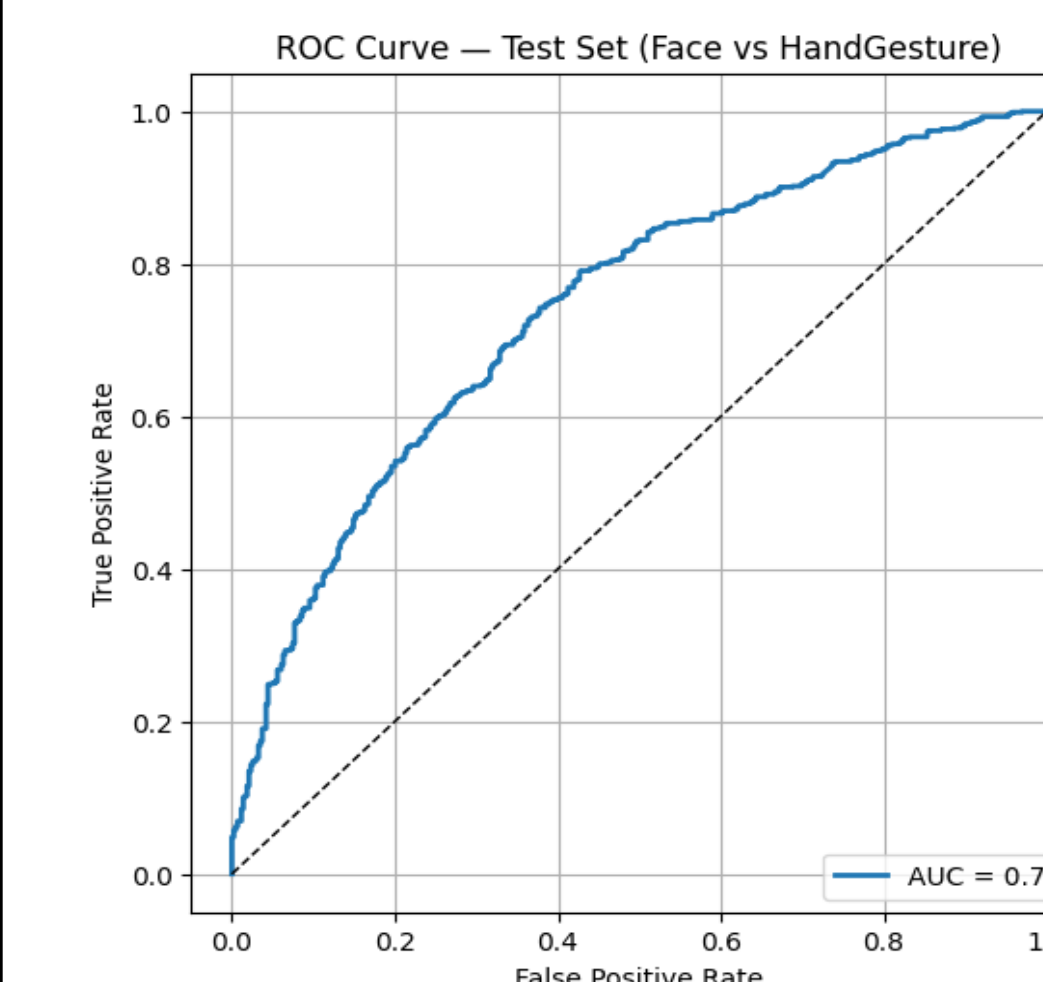
- **Training & Evaluation:** Data were split into training, validation, and test sets. Models were trained to minimize classification error, with performance assessed via accuracy, ROC AUC, and confusion matrices.



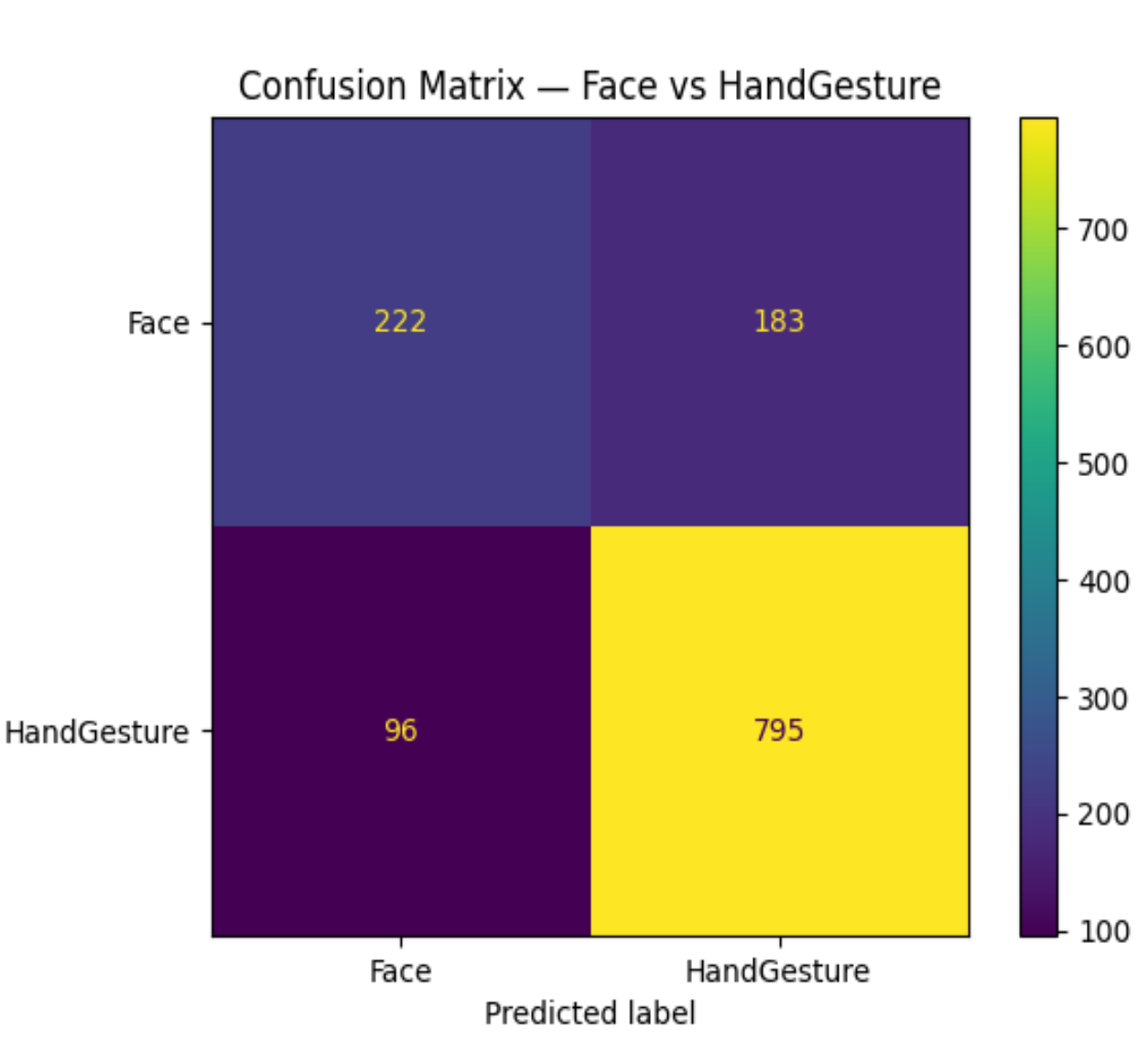
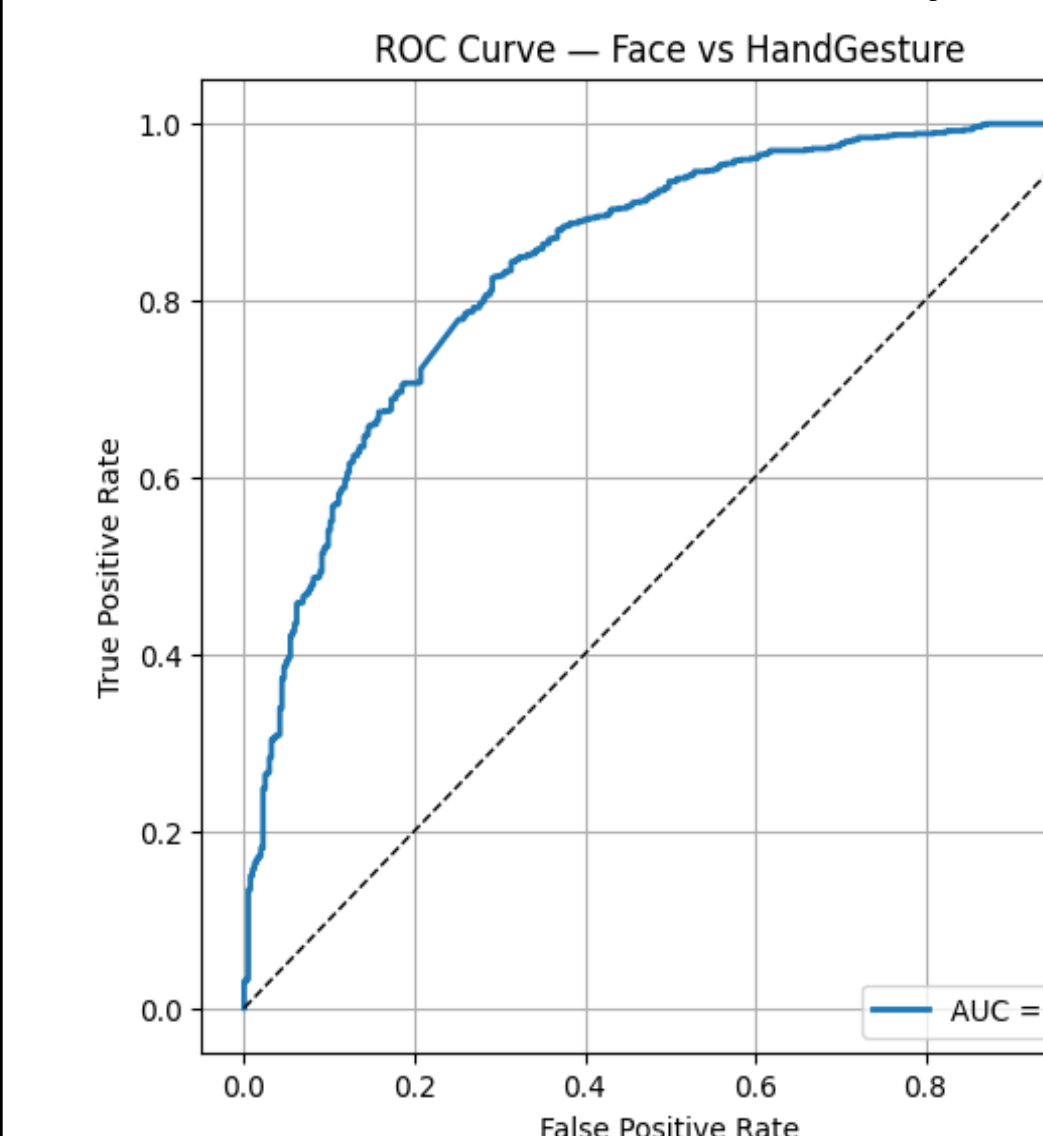
Results

Classification Performance of Each Model

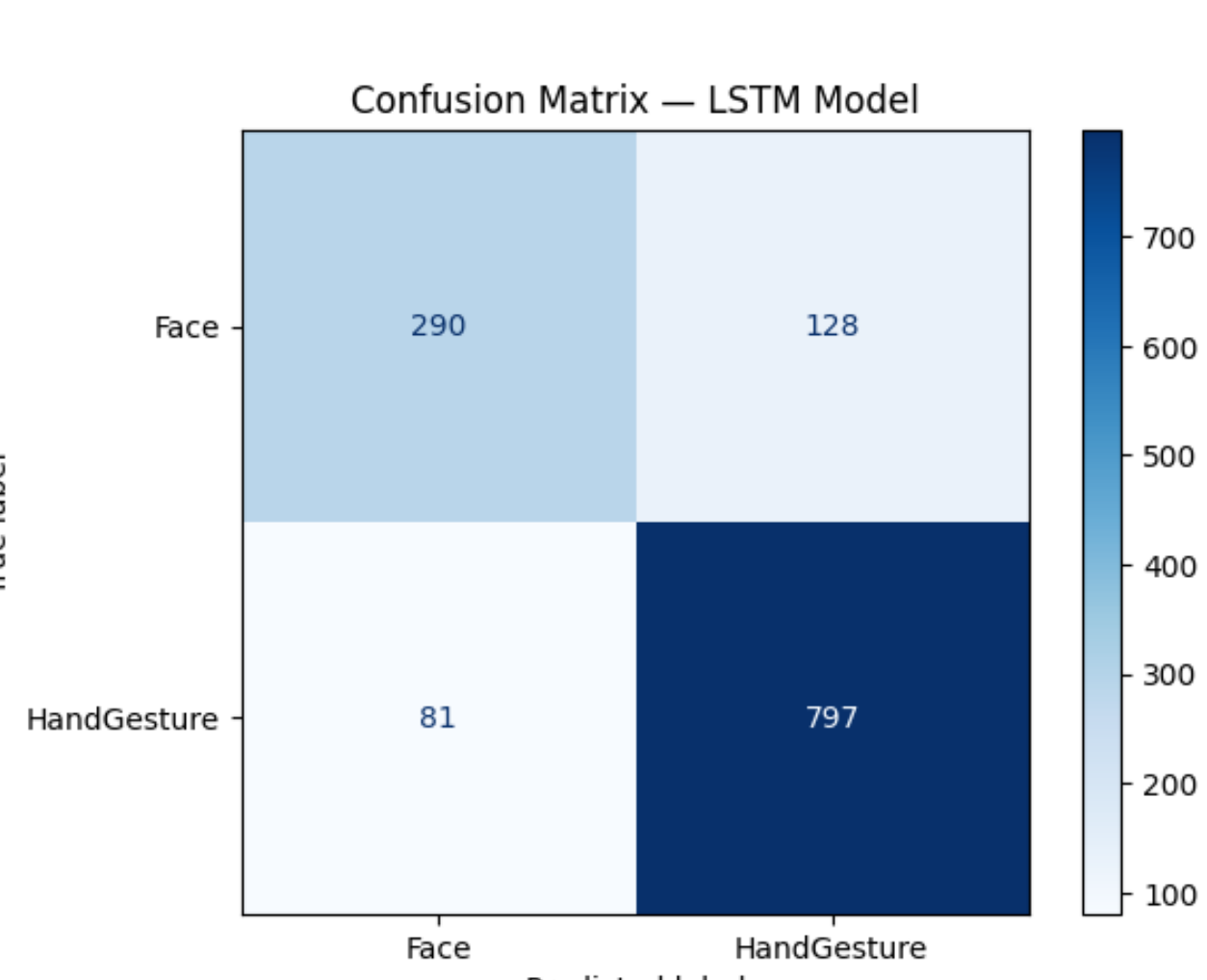
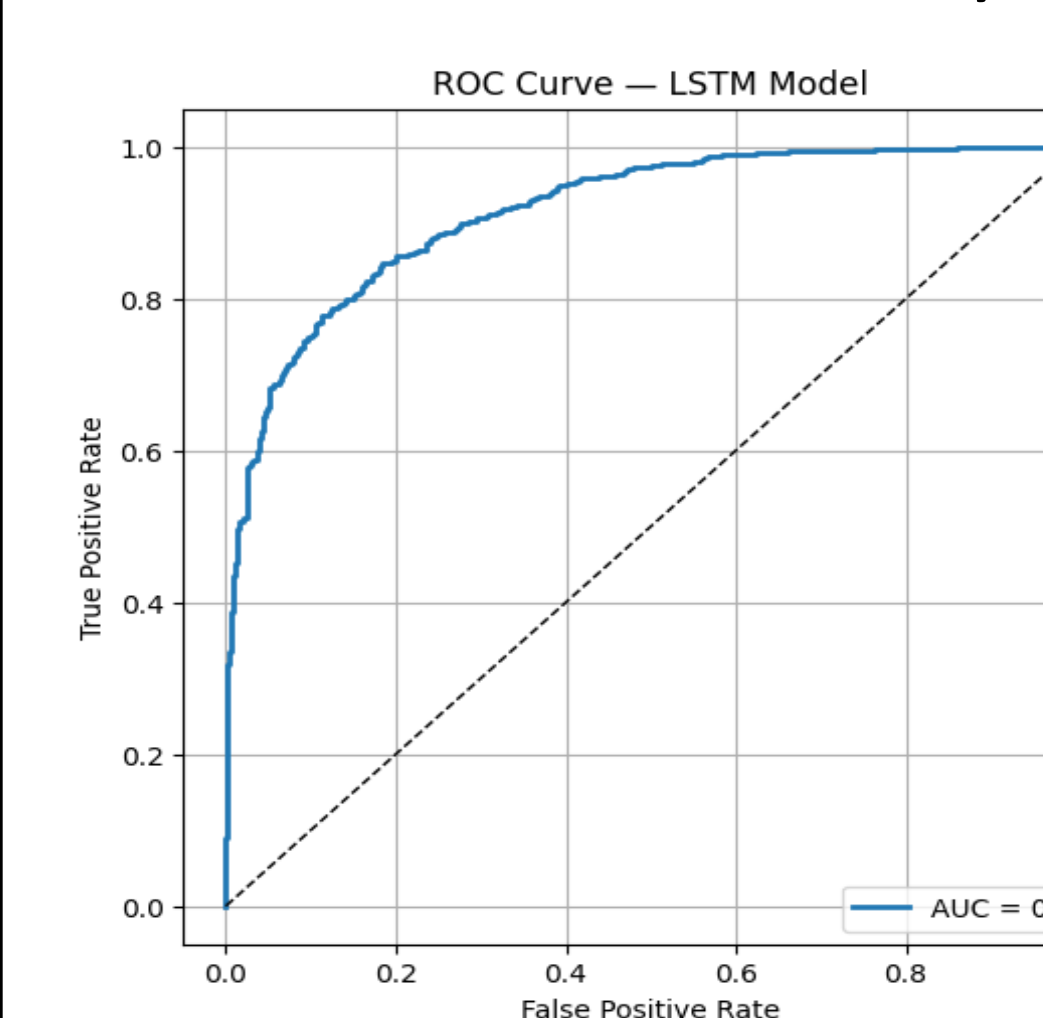
- **SVM: 70% accuracy**



- **CNN: 79% accuracy**



- **LSTM: 85% accuracy**



Discussion

- The CNN and LSTM models substantially outperformed the SVM baseline, demonstrating that deep learning can capture richer temporal dynamics in EEG and improve decoding accuracy.
- These findings highlight the potential of advanced neural networks to enhance BCI applications, though future work must focus on pinpointing the precise brain regions and temporal windows that carry the most discriminative signals for classification.

References

Soylu, F. (2017). Public Dataset: ERPs for Processing Canonical and Non-canonical Finger Numeral Representations. Harvard Dataverse. DOI:10.791