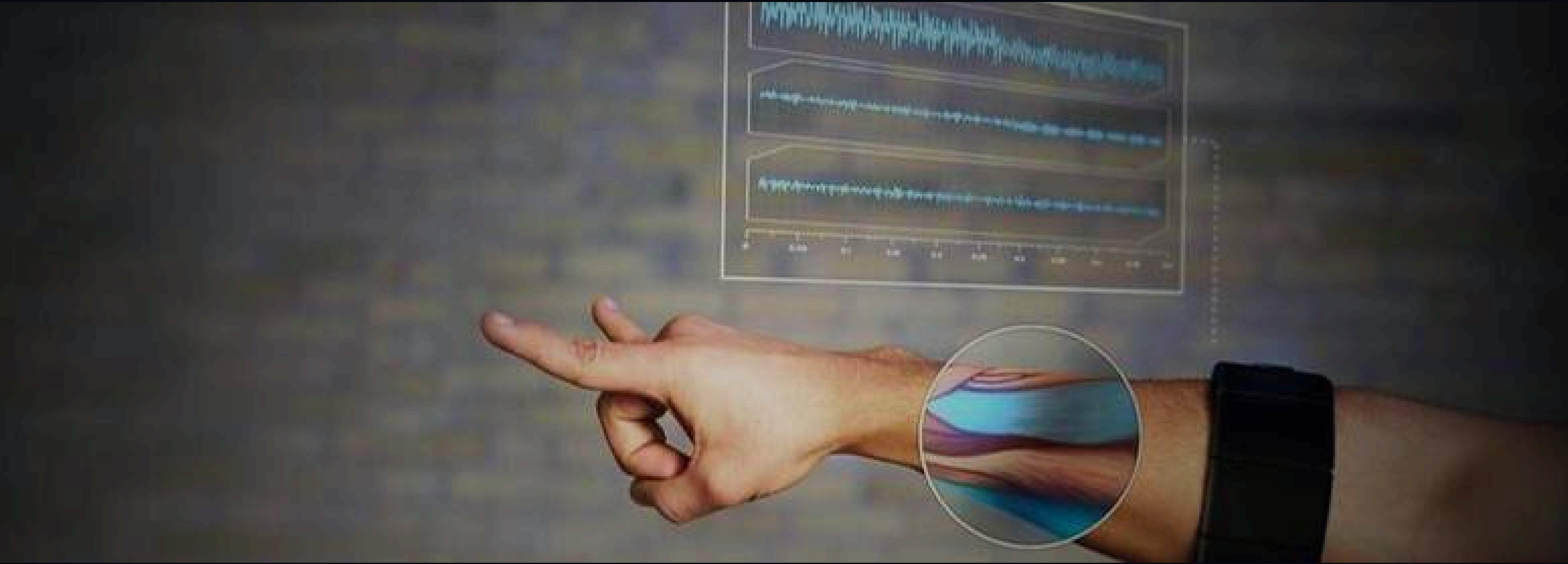
# ADVANCING HUMAN-MACHINE INTERFACE SYSTEMS THROUGH ARTIFICIAL INTELLIGENCE



AUTHOR: SAMUEL GEORGE-WHITE
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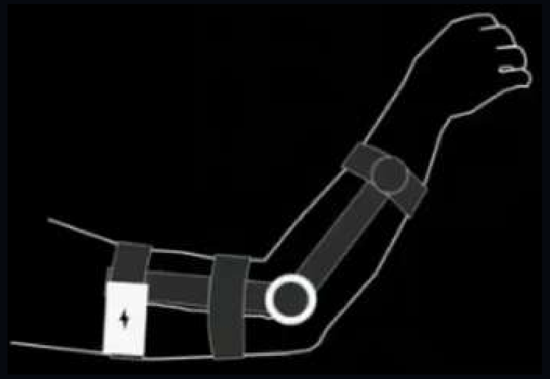
STEM THINK TANK IMPERIAL

# AUGMENTING HUMAN MOTOR CAPACITIES

# A TAXONOMY OF MOVEMENT AUGMENTATION

Power augmentation to increase the exertable forces or movement speed

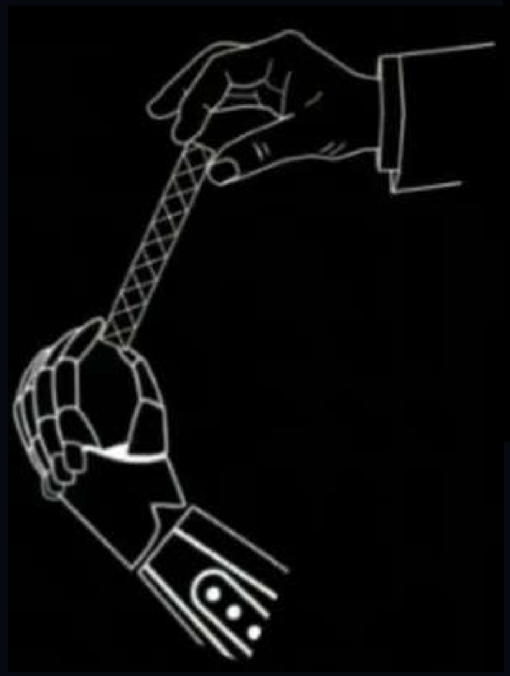


Workstation augmentation to extend the spacial reach of natural limbs

Precision augmentation increases the control precision and task performance

Degrees-of-freedom augmentation increases the number of DoFs enabling users to perform more complex tasks than with the naural DoFs alone

Task

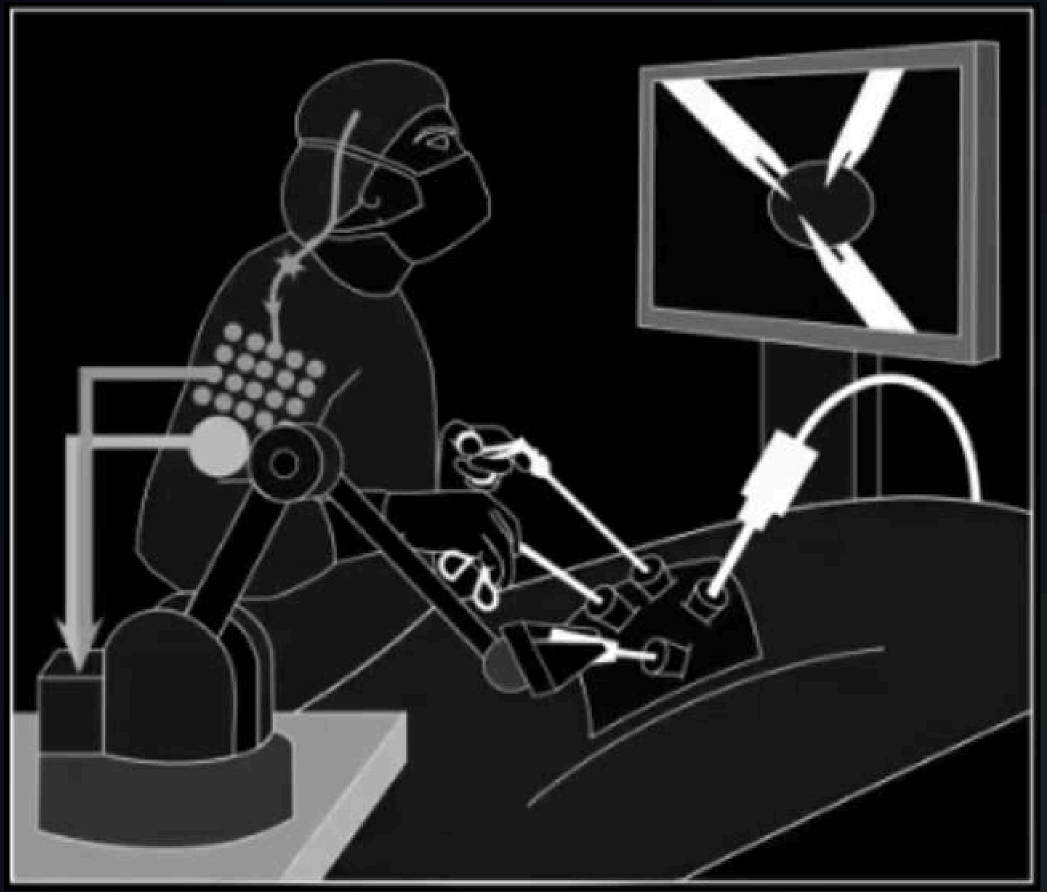


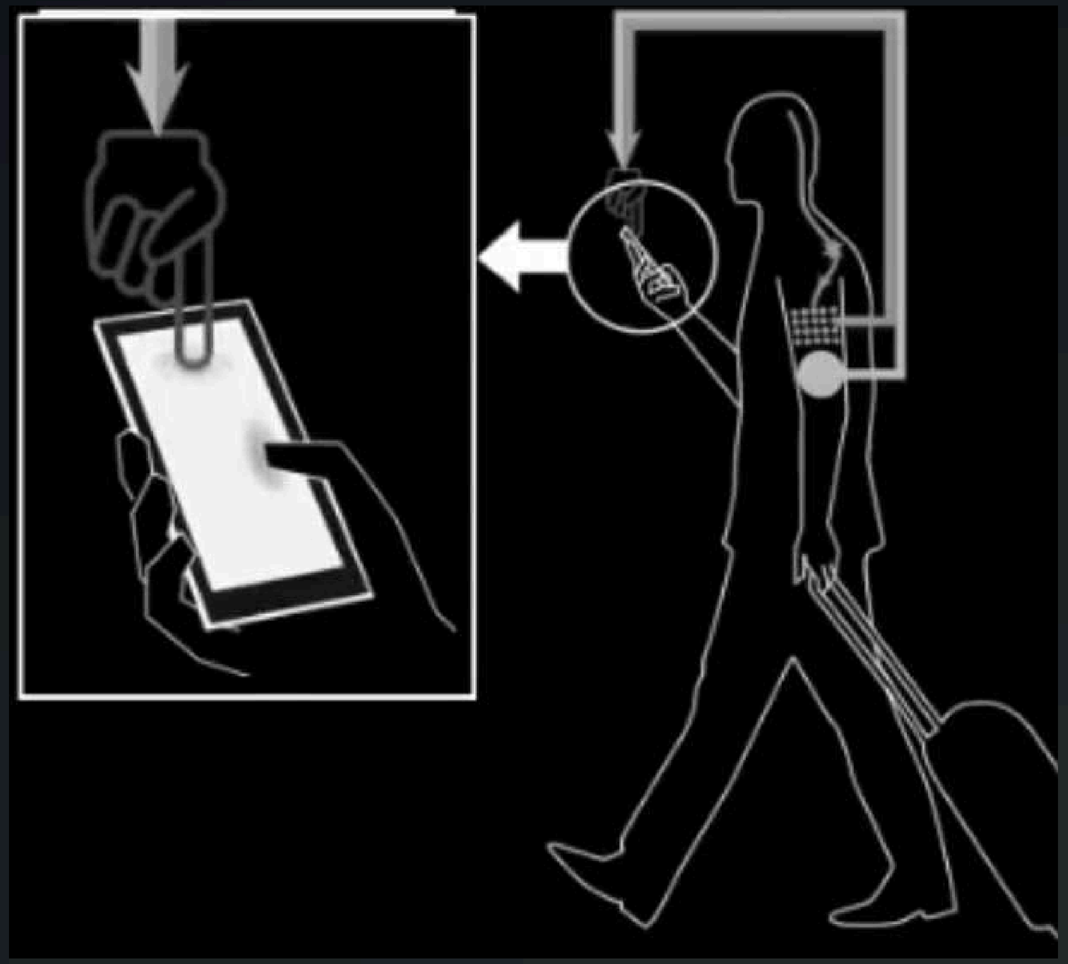
Autonomous

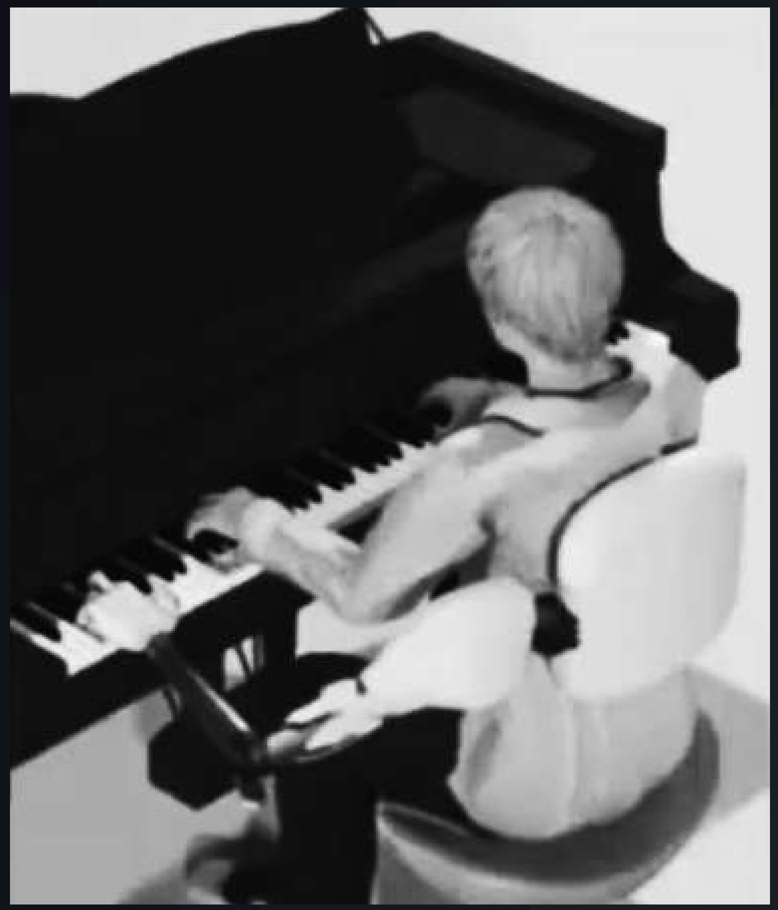
Whole-body

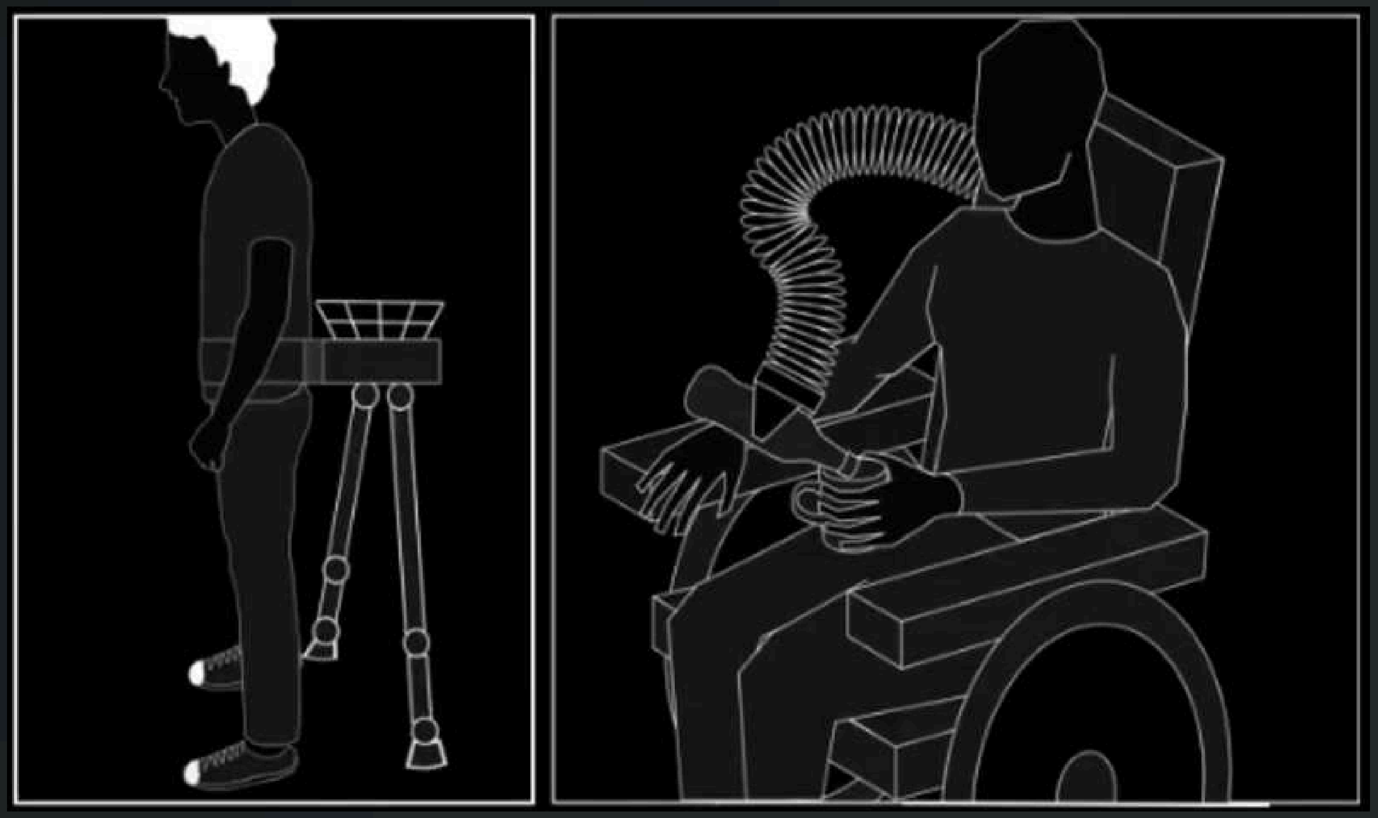
# APPLICATIONS

- Medical Interventions
- Use of computers/mobile devices
- Paralysed patients with residual movement abilities
- Day-to-day activities e.g. playing an instrument









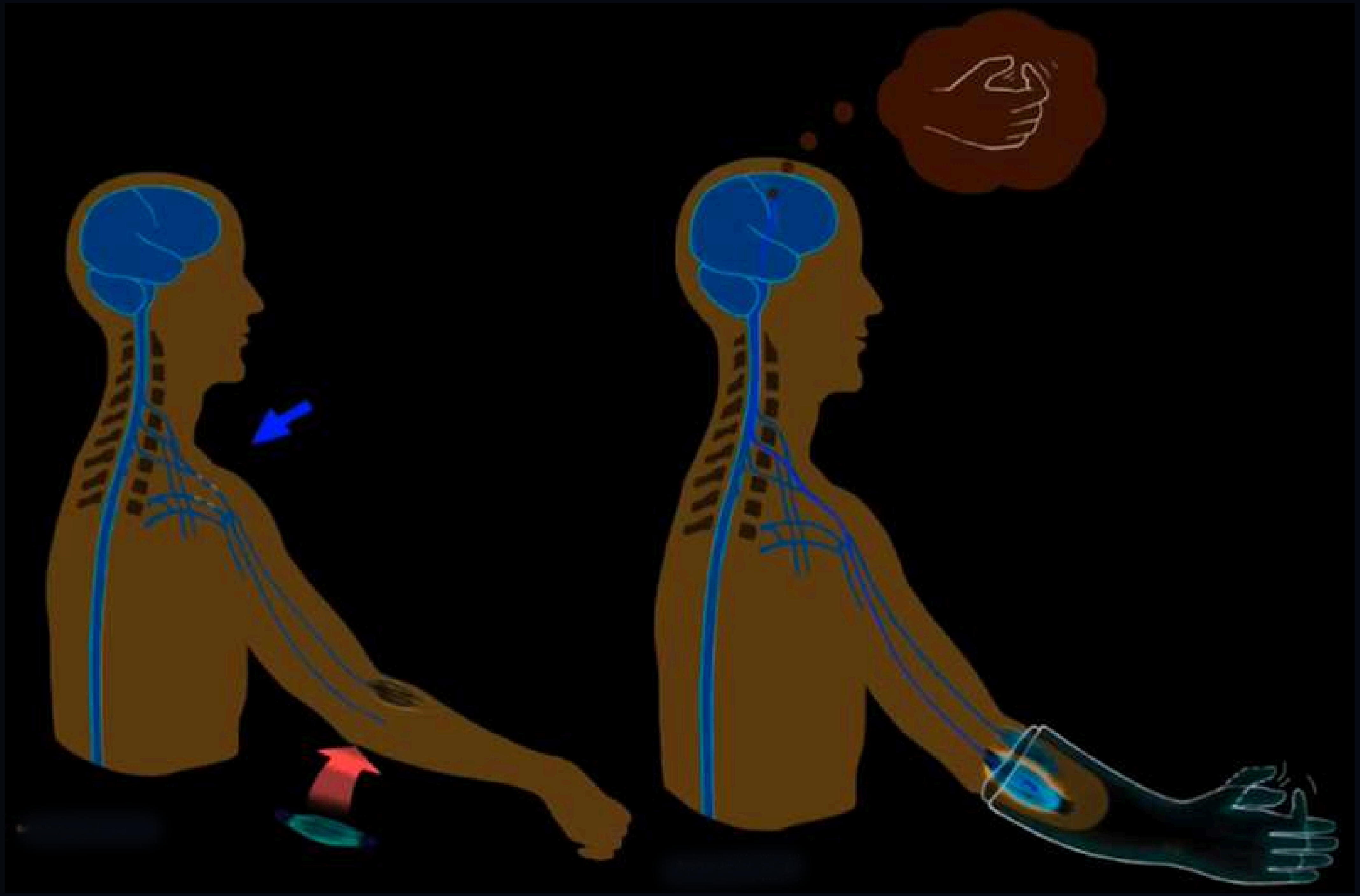
# BIONICS

# BIONIC HANDS AND ARMS IN PRINCIPLE CAN BE STRONGER, FASTER AND CAN SENSE WITH HIGHER ACCURACY THAN BIOLOGICAL ONES

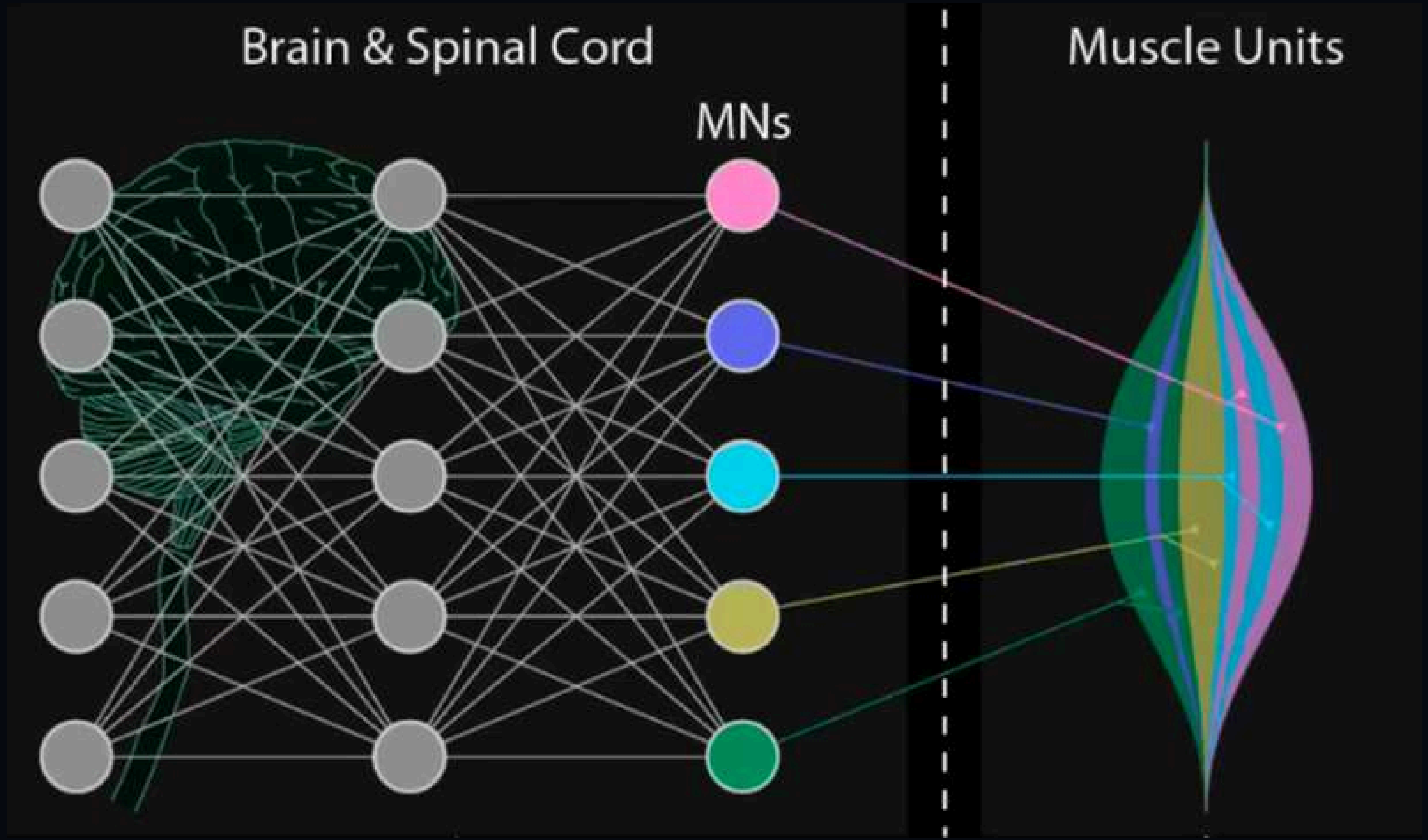
Open Bionics Hero Arm

# THE GAP BETWEEN AUTONOMOUS ROBOTS AND HUMAN-INTERFACED ROBOTS

# CREATING AN INTERFACE AND REPLACING THE BIOLOGICAL HAND

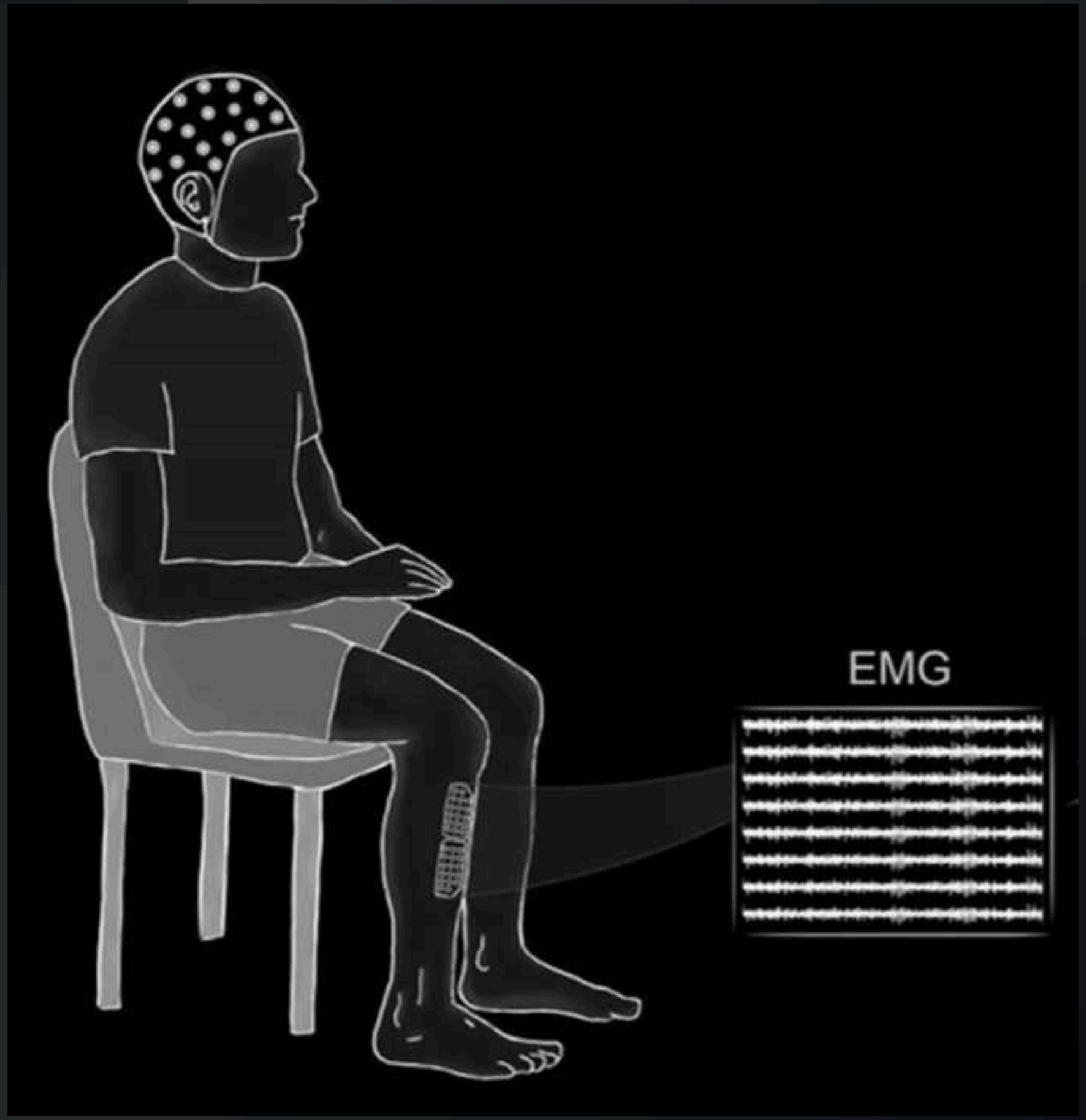


# BIOLOGICALLY INSPIRED ARTIFICIAL CLASSIFIER NETWORK



# METHODOLOGY: DATA COLLECTION

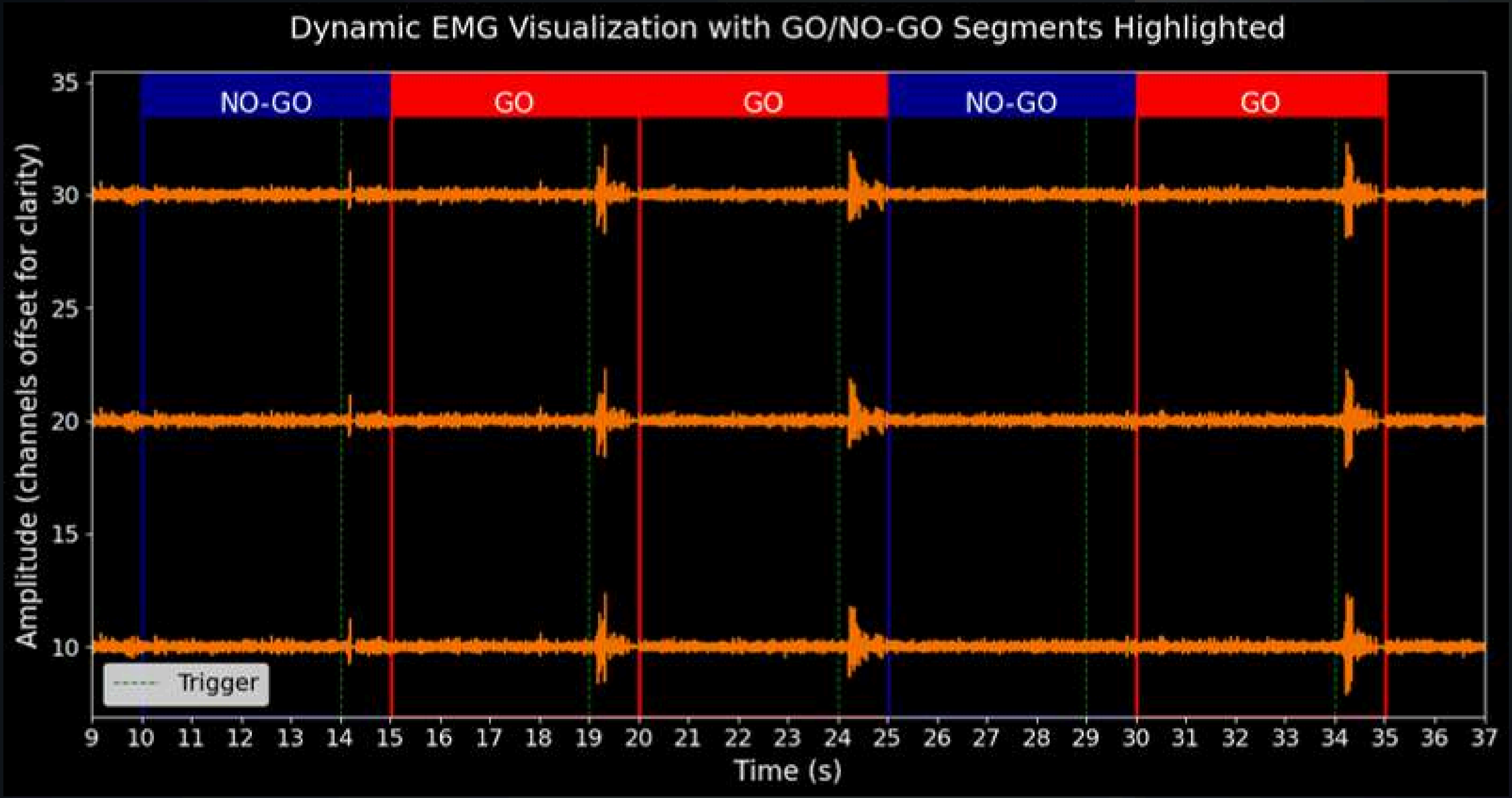
- **Overview**: The study examined neural input modulations during movement cancellation using a “GO/NO-GO” task.
- **Participants**: 12 male subjects (ages 21–38); ethical approval and consent obtained.
- **Setup**: EEG (31 electrodes) and high-density EMG (64 channels) recorded from the tibialis anterior muscle. Participants performed isometric ankle dorsiflexion at 10% MVC.
- **Task**: In “GO” trials, a ballistic contraction was performed. In “NO-GO” trials, force was maintained at 10% MVC. Each block had 35 trials, with fixed timing for auditory cues.



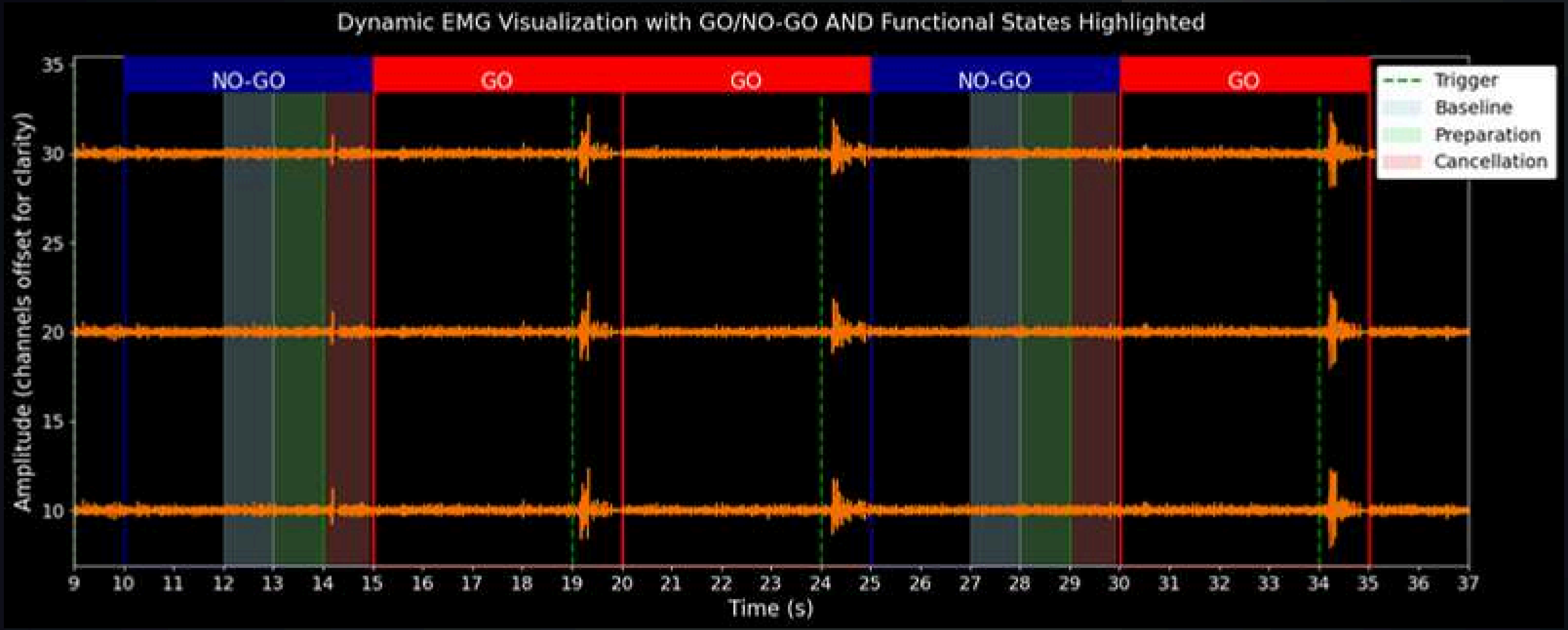

[2]

Zicher, B., et al. (2024). Journal of Neural Engineering, 21(056039). https://doi.org/10.1088/1741-2552/ad8835

# GO/NO-GO EXPERIMENT PARADIGM



# FUNCTIONAL STATES



# METHODOLOGY: DATA PREPROCESSING

## INITIAL PIPELINE

**Segment data**

Select NO-GO regions
Extract Baseline,
Preparation and
Cancellation windows

Shape: Participant, Class,
no. of trials, samples,
channels
(7, 3, X, 2048, 64)

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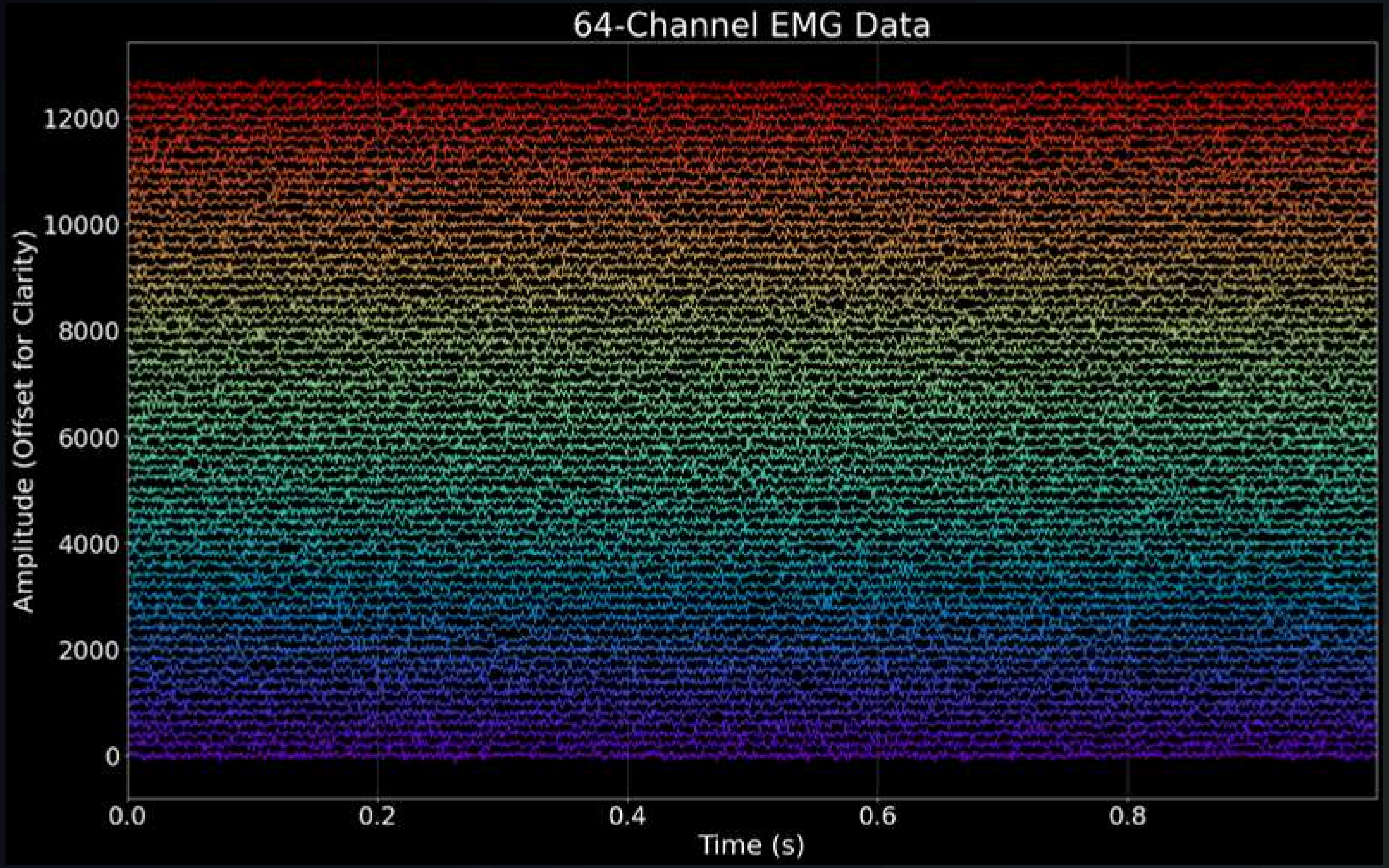
**Channel Reduction through PCA**

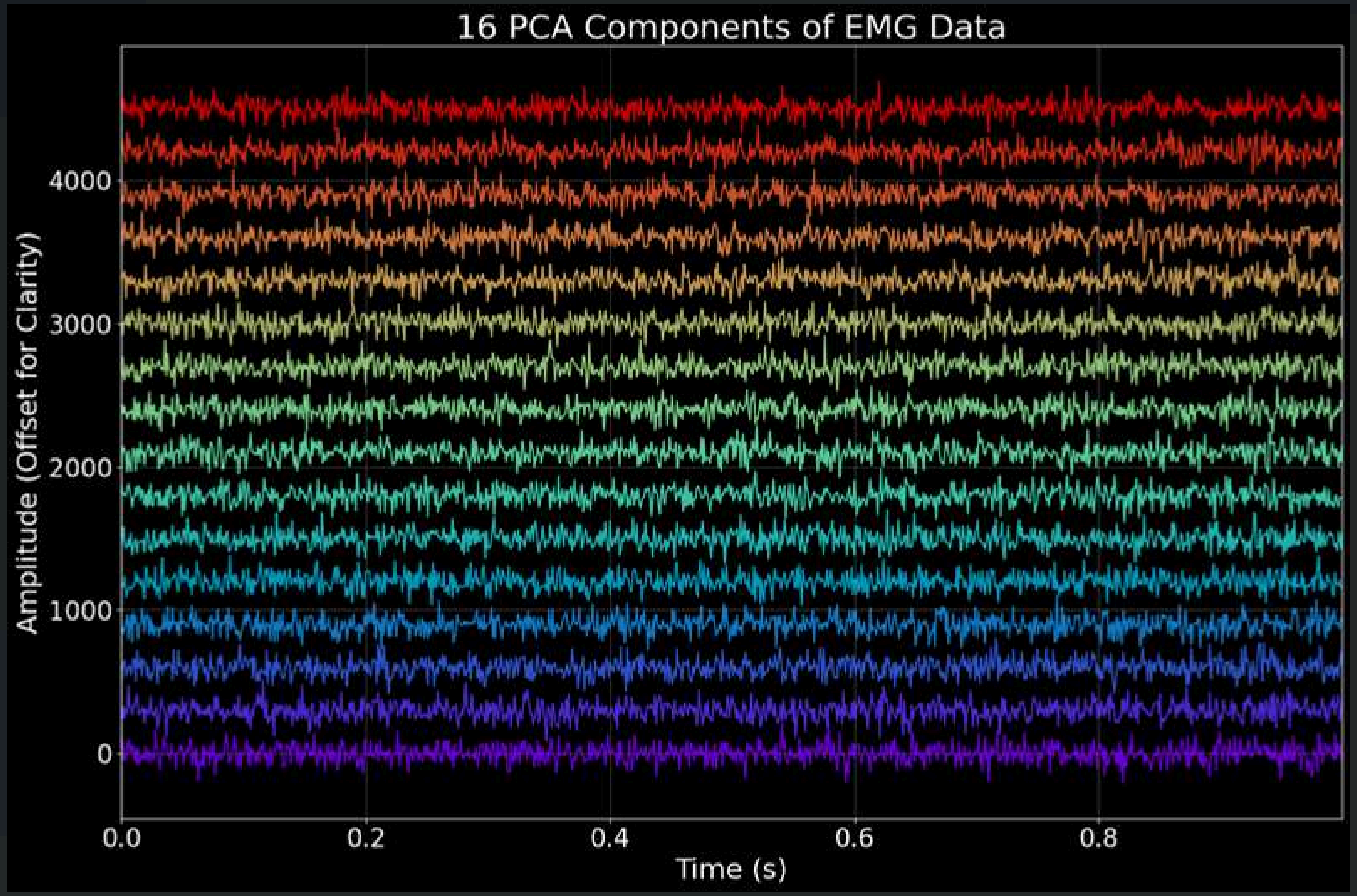
Shape: (7, 3, X, 2048, 16)

# PRINCIPAL COMPONENT ANALYSIS




PCA Reduction

64 Channel EMG to 16 PCA Components



# METHODOLOGY: DATA PREPROCESSING

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Shape: Participant, Class, no. of trials, samples, channels
(7, 3, X, 2048, 64)

**Channel Reduction through PCA**

Shape: (7, 3, X, 2048, 16)

**Filtering and Normalisation**

Bandpass filtering (13-30Hz)

Downsample to 512Hz

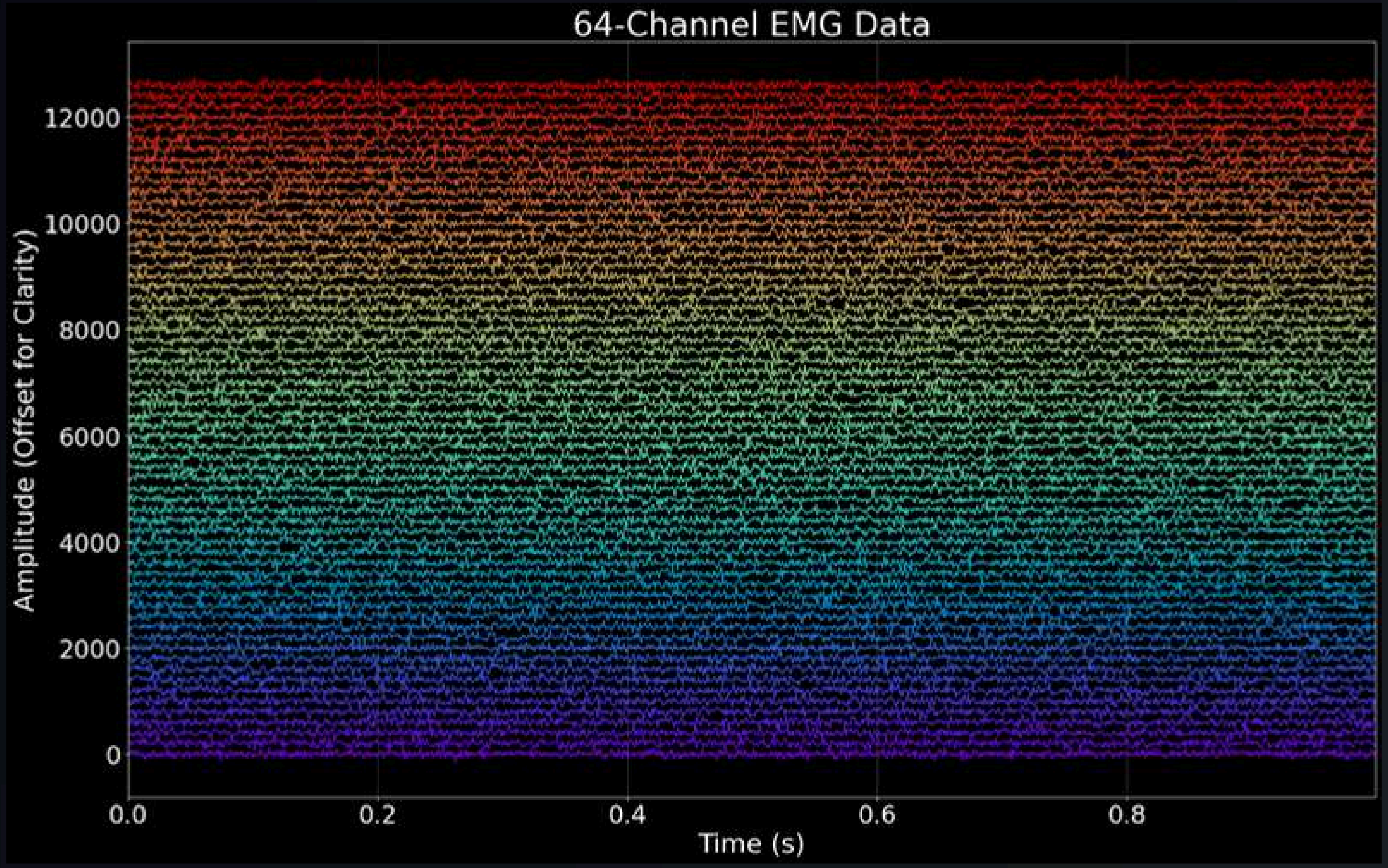
Amplitude and Z-score normalization

Shape:
(7, 3, X, 512, 16)

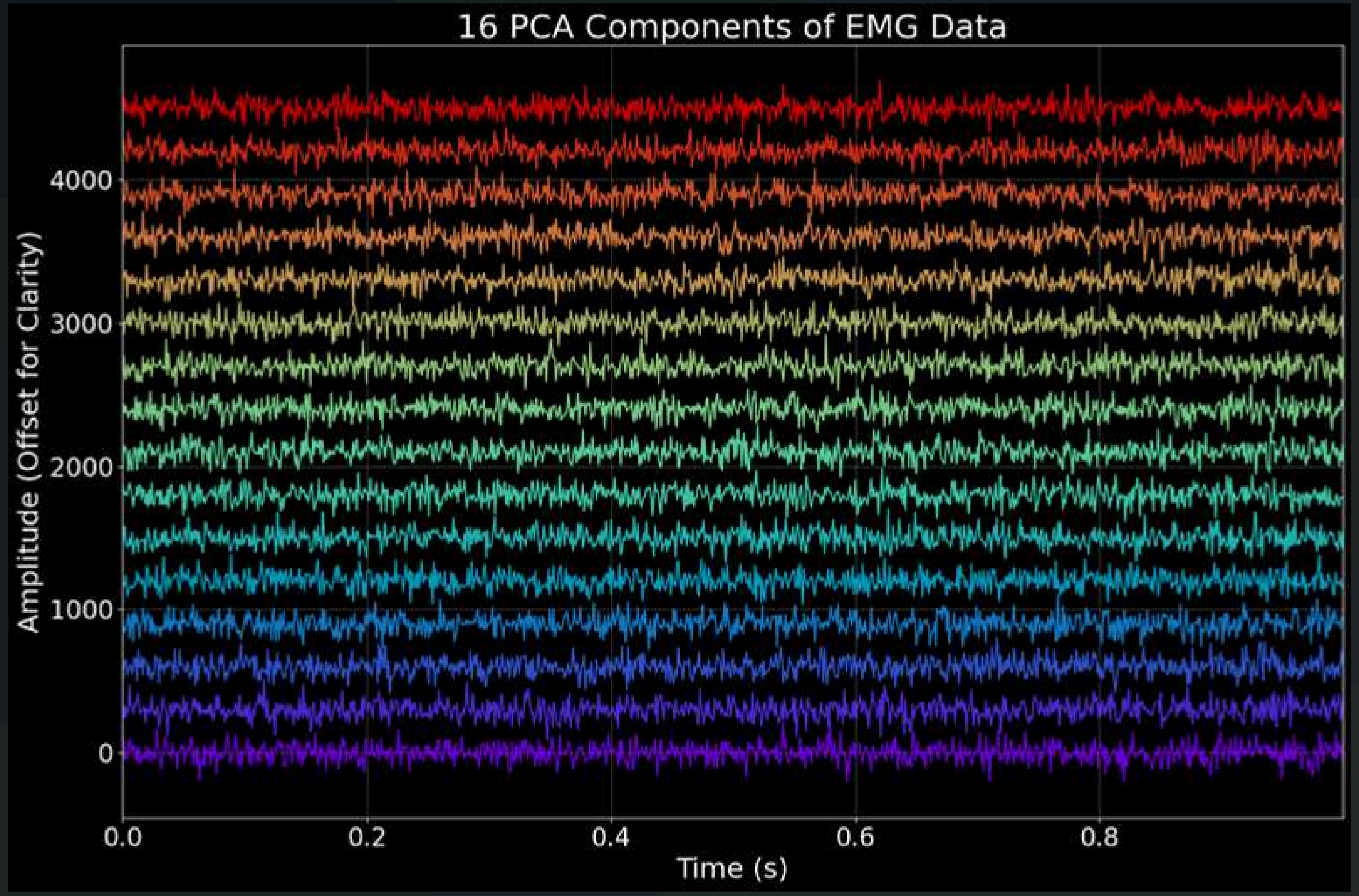
**Data augmentation**

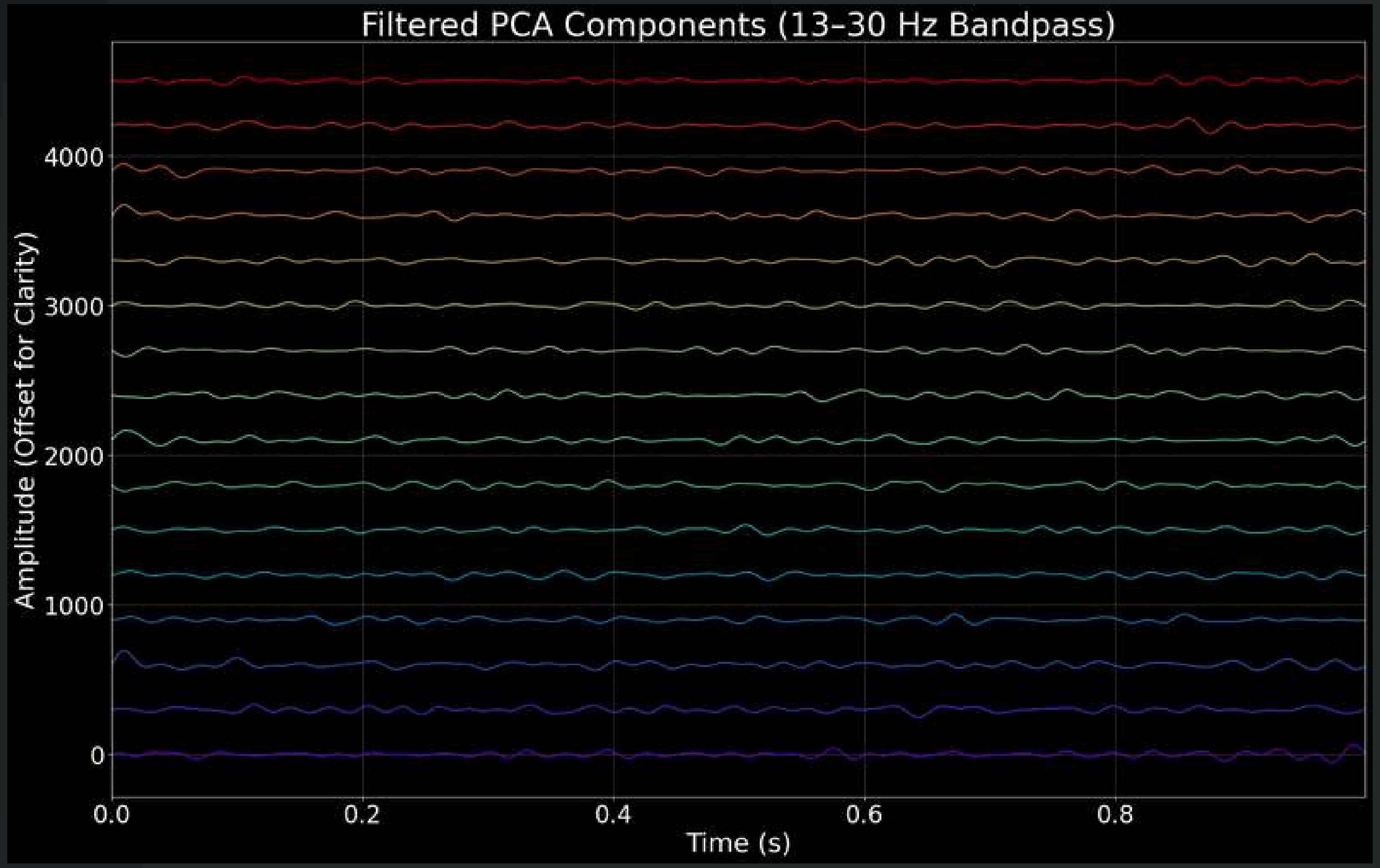
Jittering and slight augmentations to frequency range of randomly selected trials

Shape:
(7, 3, X, 512, 16)




PCA Reduction




Beta Band Bandpass Filtering (13-30Hz)

# FILTERING AND NORMALISATION

- Amplitude normalisation per trial
- Z-score normalizsation
- Data augmentation (jittering, slight augmentations to frequency filtering)

# METHODOLOGY: DATA PREPROCESSING

**Segment data**

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Shape: Class, no. of trials, samples, channels
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(7, 3, X, 512, 16)

**Data augmentation**

Jittering and slight augmentations to frequency range of randomly selected trials

Shape: (7, 3, X, 512, 16)

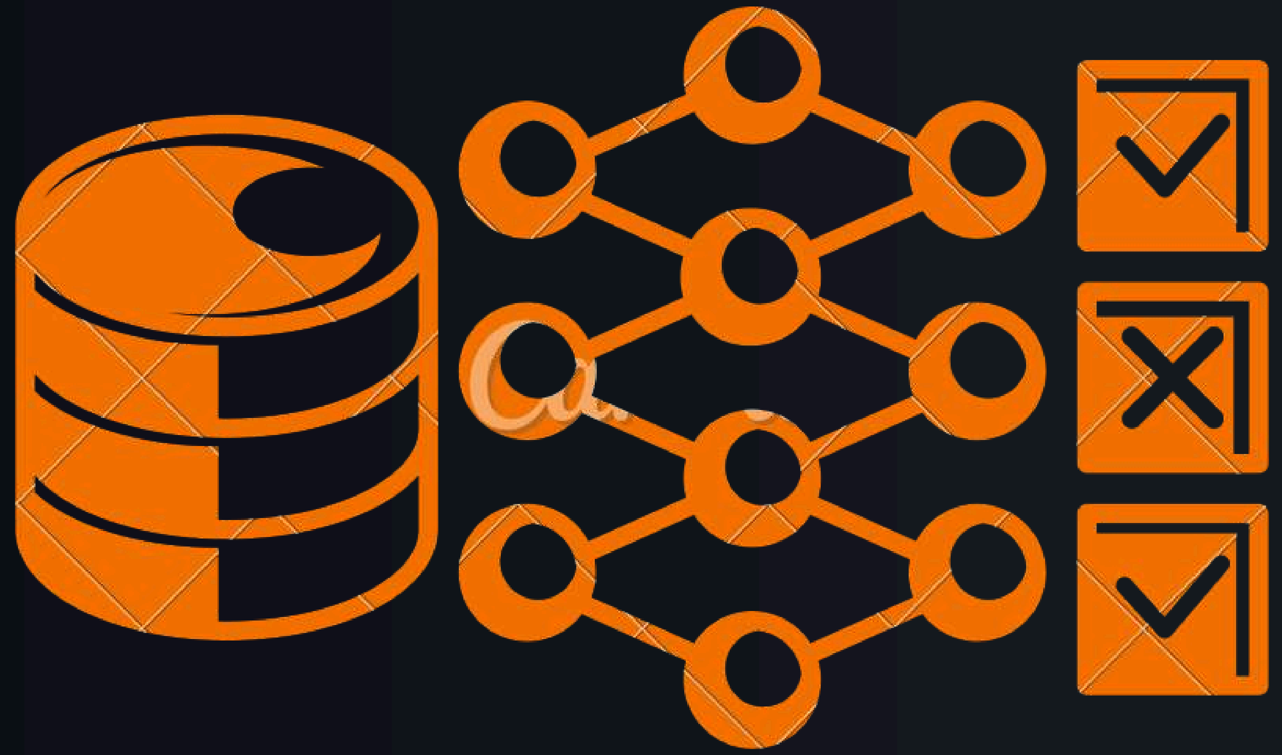
**Beta Power**

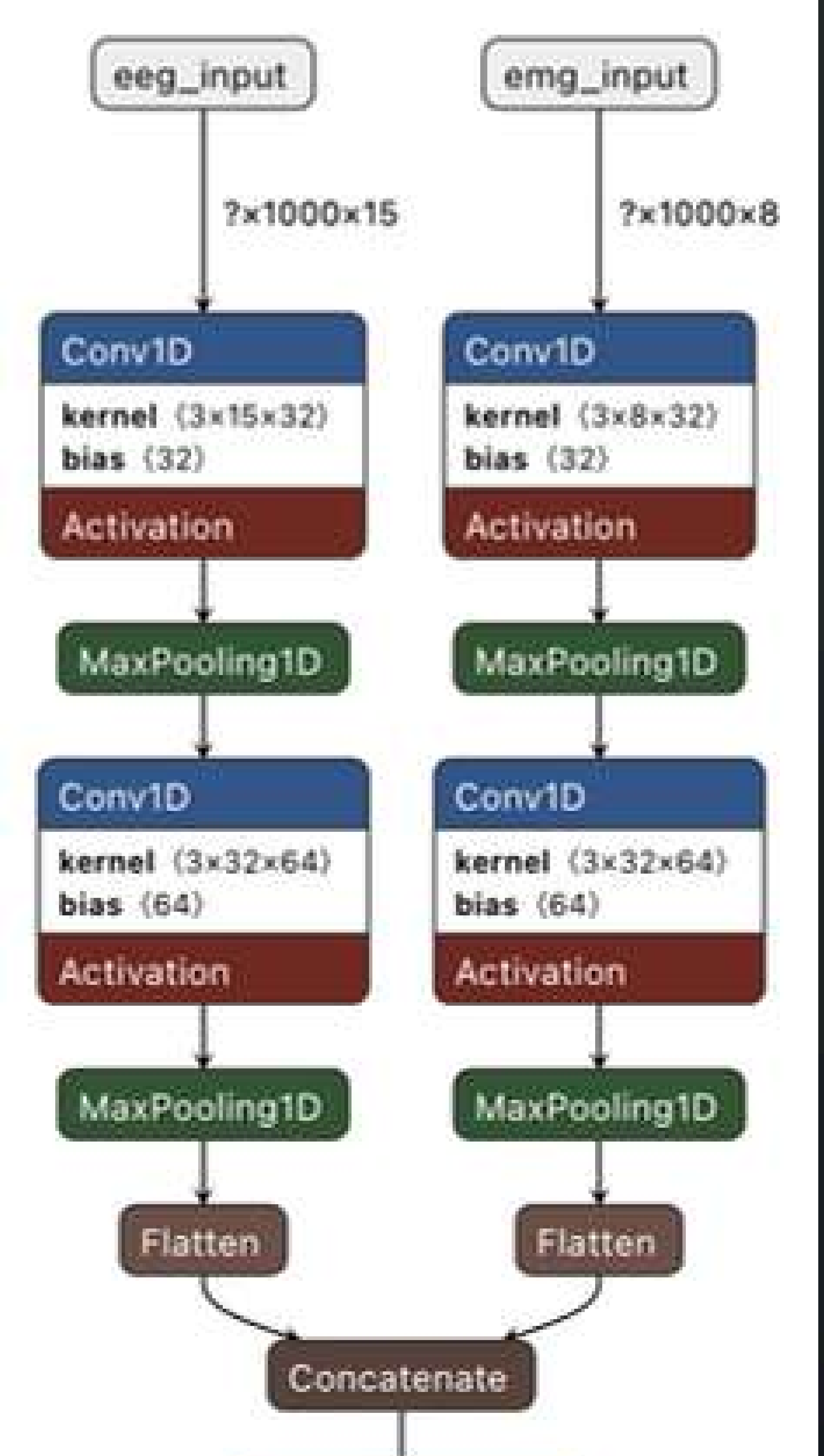
Compute Beta Power across channels

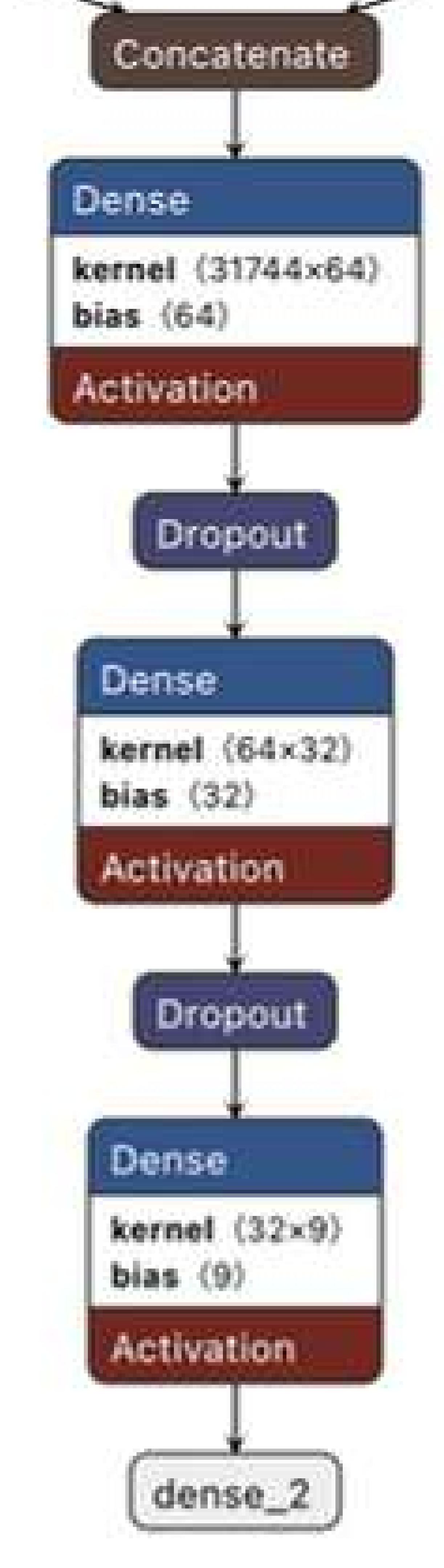
Smooth beta power curves

Shape: (7, 3, X, 512, 1)

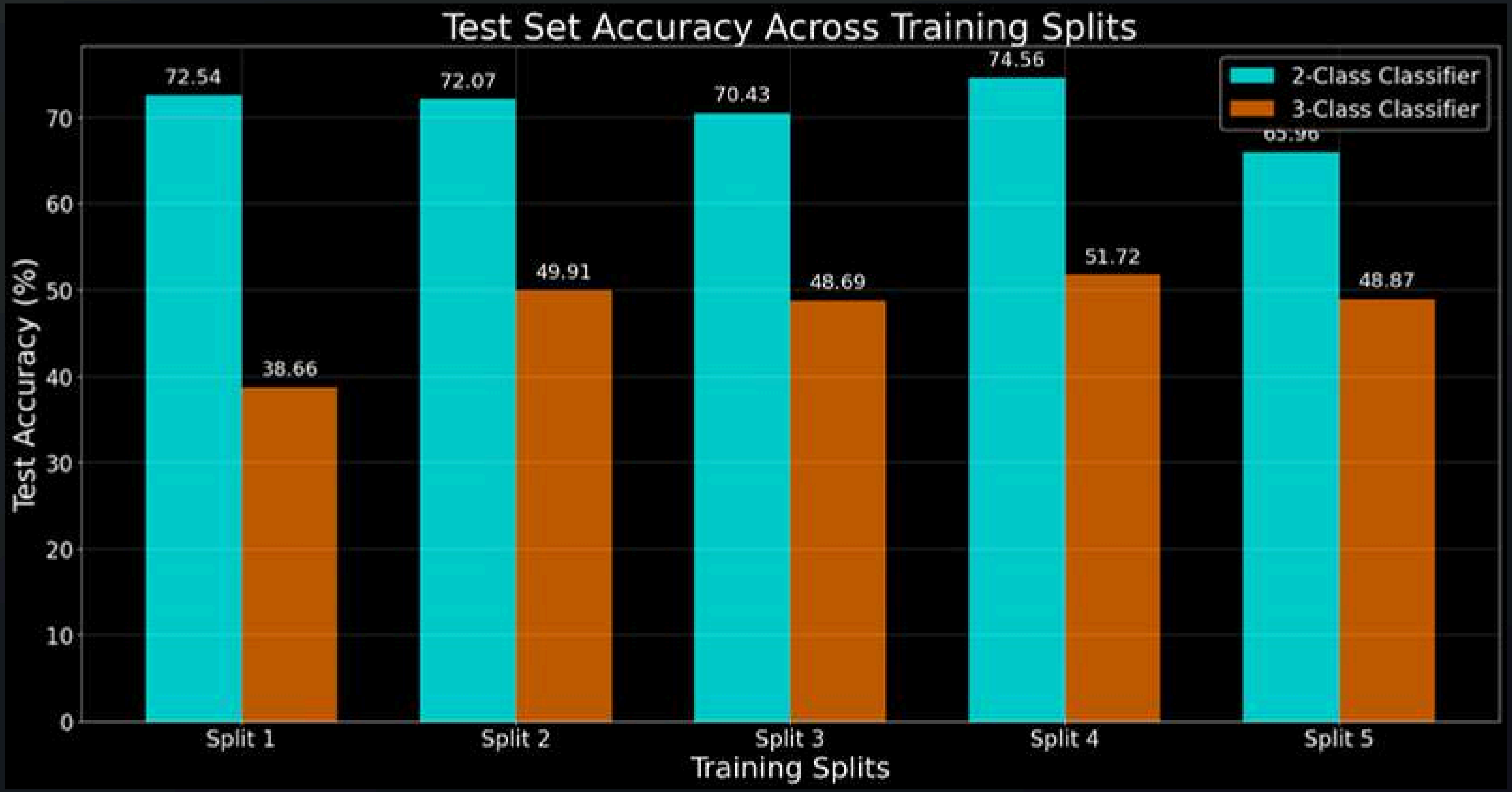
# METHODOLOGY: CLASSIFIER NETWORK





# INITIAL RESULTS: ACCURACY




2-Class Average Accuracy: 72.4%
3-Class Average Accuracy: 49.6%

# INITIAL RESULTS: LOSS

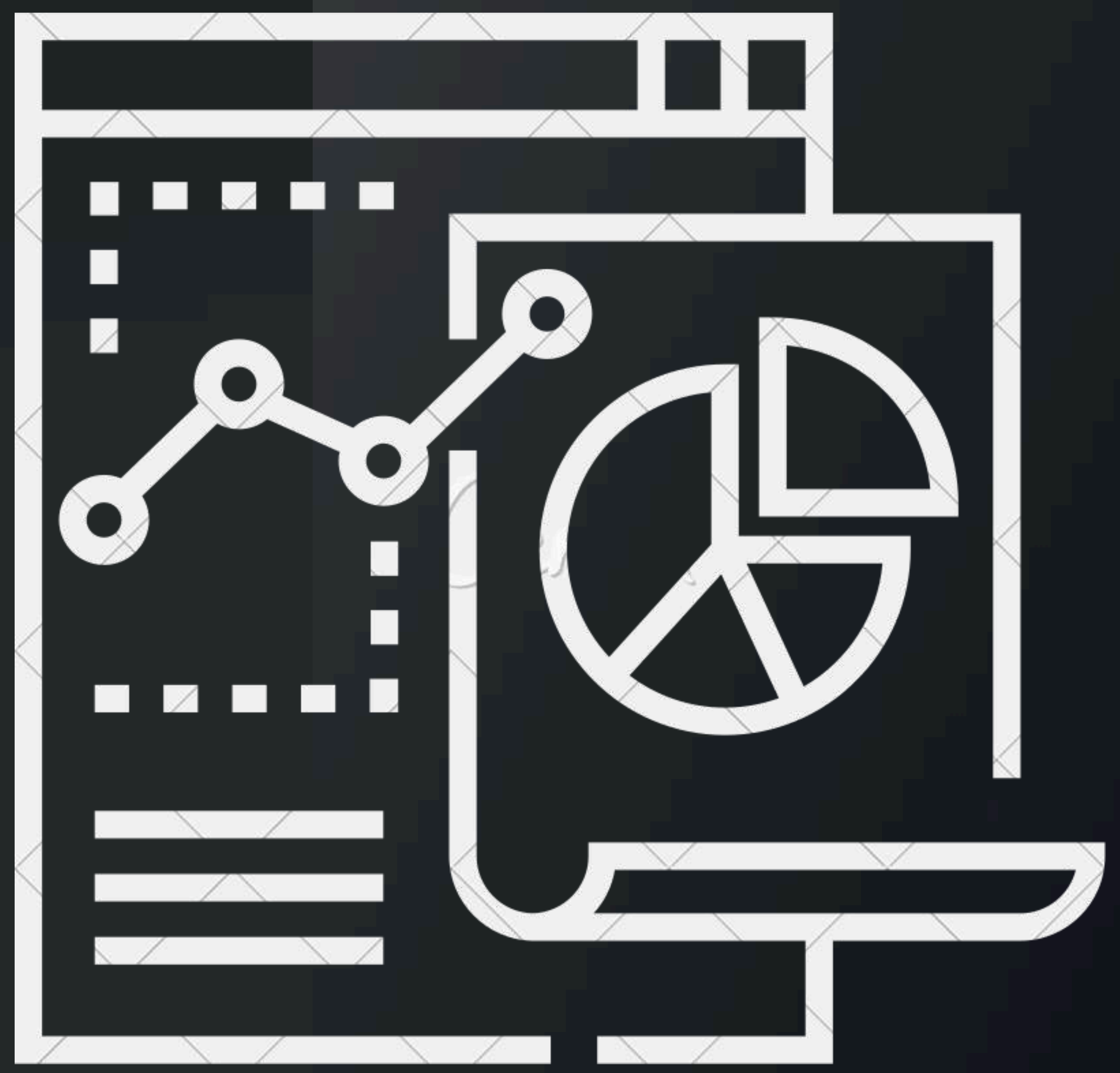

2-Class Average Loss: 0.532
3-Class Average Loss: 0.900

# ANALYSIS: GRADCAM

**Gradient-weighted Class Activation Mapping (GradCAM)** is a visualization technique used to understand and interpret the decisions made by convolutional neural networks (CNNs).

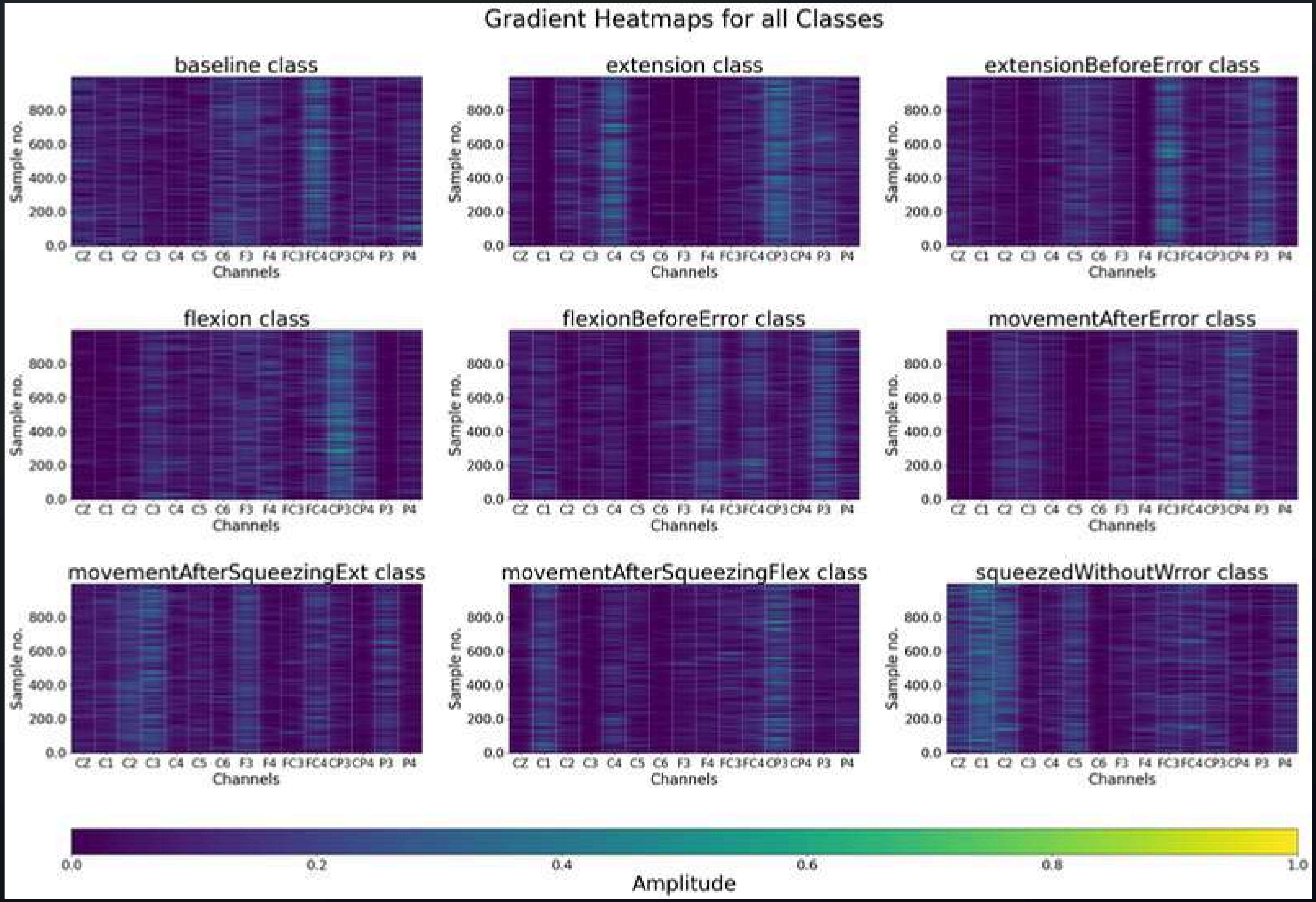
GradCAM highlights the regions in the input data that are most influential in predicting a particular class, providing insights into the model's decision-making process.

GradCAM works by computing the **gradient** of the predicted class score with respect to the activations of a convolutional layer. These gradients are then weighted by the average gradient across the spatial dimensions.



# ANALYSIS: GRADCAM

Gradient Heatmap Visualization



# CURRENT ADJUSMENTS

**Leverage Temporal Context**

- Use the fact that the preparation class is always followed by cancellation.
- Explore merging “Preparation” and “Cancellation” classes into a single class.
- Perform comparisons:
- Cancellation vs Baseline
- Baseline vs Preparation + Cancellation
- Introduce a sliding window approach to capture dynamic changes.

**Alternative Input Configurations**

- Use all 64 channels directly as classifier input (bypass PCA).
- Calculate the mean of the square of the 64 channels as input instead of all individual channels.
- Evaluate classifier performance with and without PCA applied to the full set of 64 channels.
- Try calculating PCA across all trials collectively instead of per trial.

**Ablation Studies**

- Conduct stepwise ablations of preprocessing steps (e.g., filtering, normalization).
- Measure and compare classifier performance after removing or modifying specific steps.
- Present findings in a key or matrix format for clarity.

**Alternative Techniques**

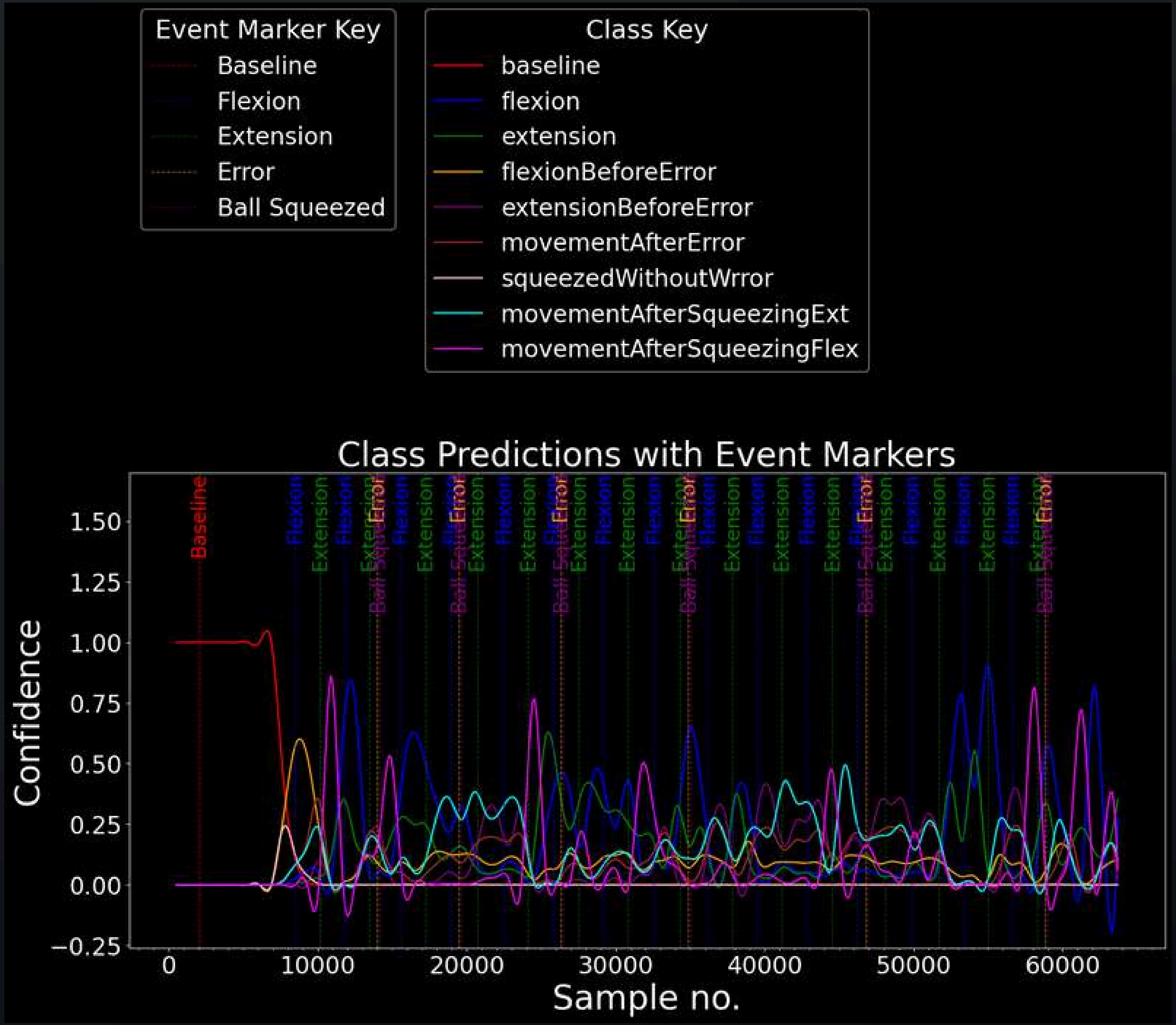
- Apply KL Transform or Maximum Relevance Minimum Redundancy (mRMR) to evaluate feature selection efficacy.
- Compare results of KL Transform and mRMR techniques against PCA.

# CLASSIFIER NETWORK: KEY CLASSES

| Key | Label | Description |
|---|---|---|
| 0 | Baseline | Baseline - Baseline run without errors was also included to establish a control dataset. |
| 1 | Flexion | Flexion - Flexion run without errors |
| 2 | Extension | Extension - Extension run without errors |
| 3 | Flexion Before Error | Flexion before err - Flexion run up until error is introduced |
| 4 | Extension Before Error | Extension before err - Extension run up until error is introduced |
| **5** | **Movement After Error** | Movement After Error - Movement after error is detected where **subject is preparing to execute movement** (squeeze the ball) |
| 6 | Squeezed Without Error | Squeezed Without Error - run where participant squeezed the ball without mistake/without an error |
| 7 | Movement After Squeezing Extension | Movement After Squeezing Extension - participant resuming extension run after ball squeezed |
| 8 | Movement After Squeezing Flexion | Movement After Squeezing Flexion - participant resuming flexion run after ball squeezed |

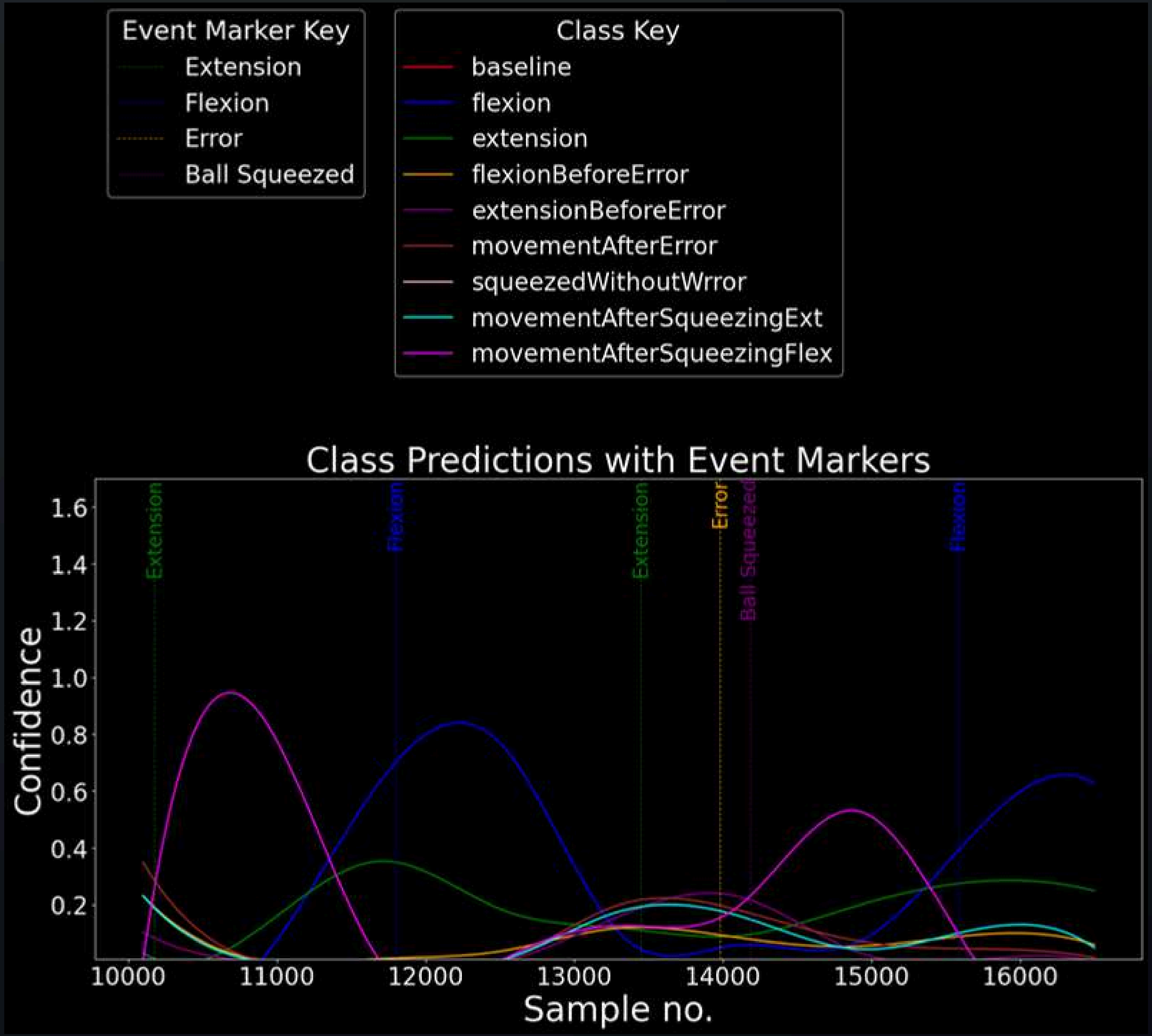
# ANALYSIS: SLIDING WINDOW

Temporal Analysis with Sliding Window - **Overview**



# ANALYSIS: SLIDING WINDOW

Temporal Analysis with Sliding Window - **Detailed view**

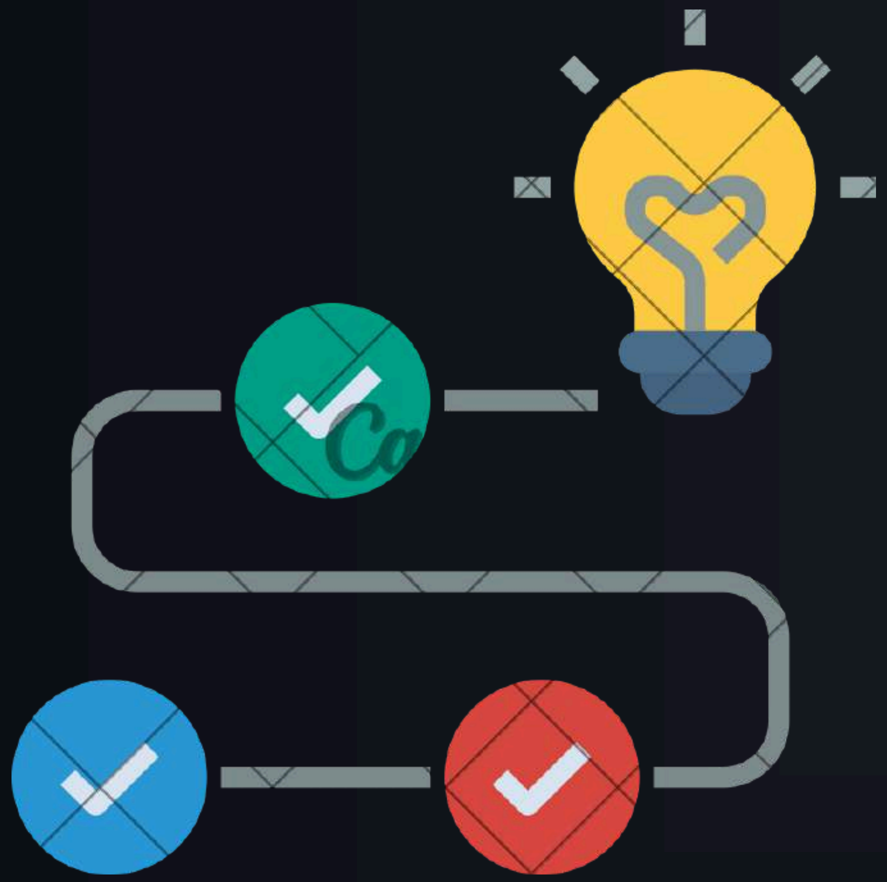


# CONCLUSION

REVIEW

1

Our preliminary results have successfully demonstrated the feasibility of decoding central nervous system (CNS) activity using non-invasive electromyography (EMG) recordings.



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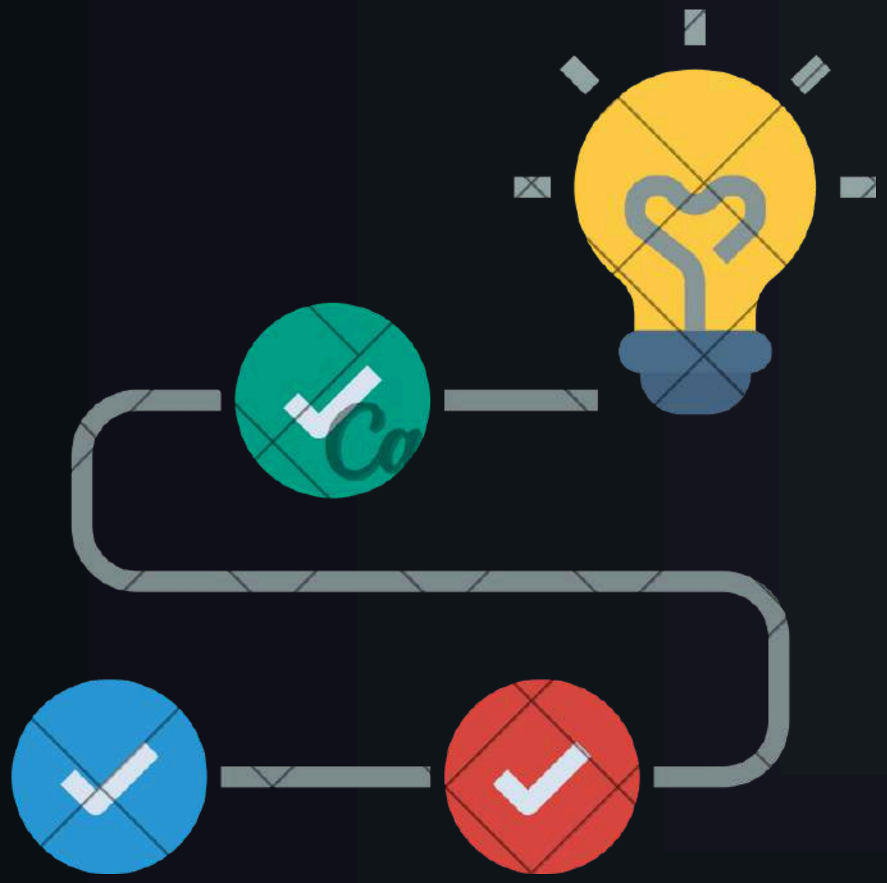

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IMPLICATIONS

2

The findings from this study have significant implications for various fields, including rehabilitation, prosthetics, and the broader field of neurotechnology, offering new insights into neural control mechanisms and paving the way for innovative human-machine interfaces (HMIs).

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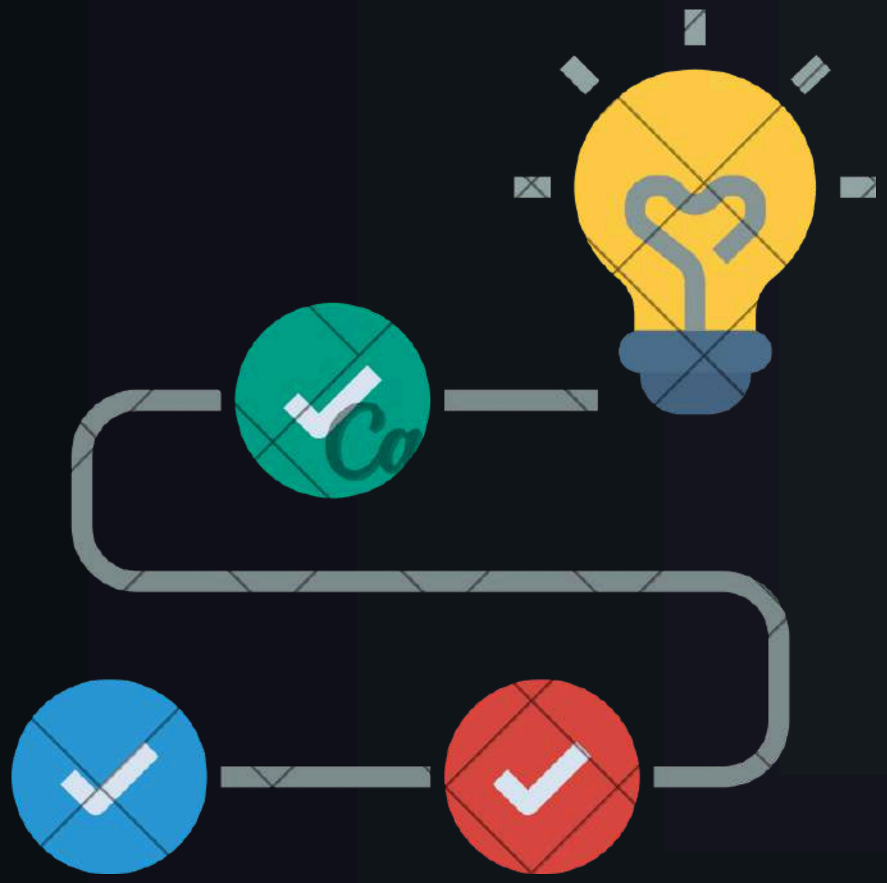

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FUTURE WORK

3

I will focus on refining the AI model to enhance its accuracy and robustness. To build on our current results, I will devise specific experiments aimed at exploiting the full potential of EMG-based CNS decoding for HMI advancements in Real Time scenarios.

# THANK YOU

QUESTIONS