EMG DATA FOR GESTURES

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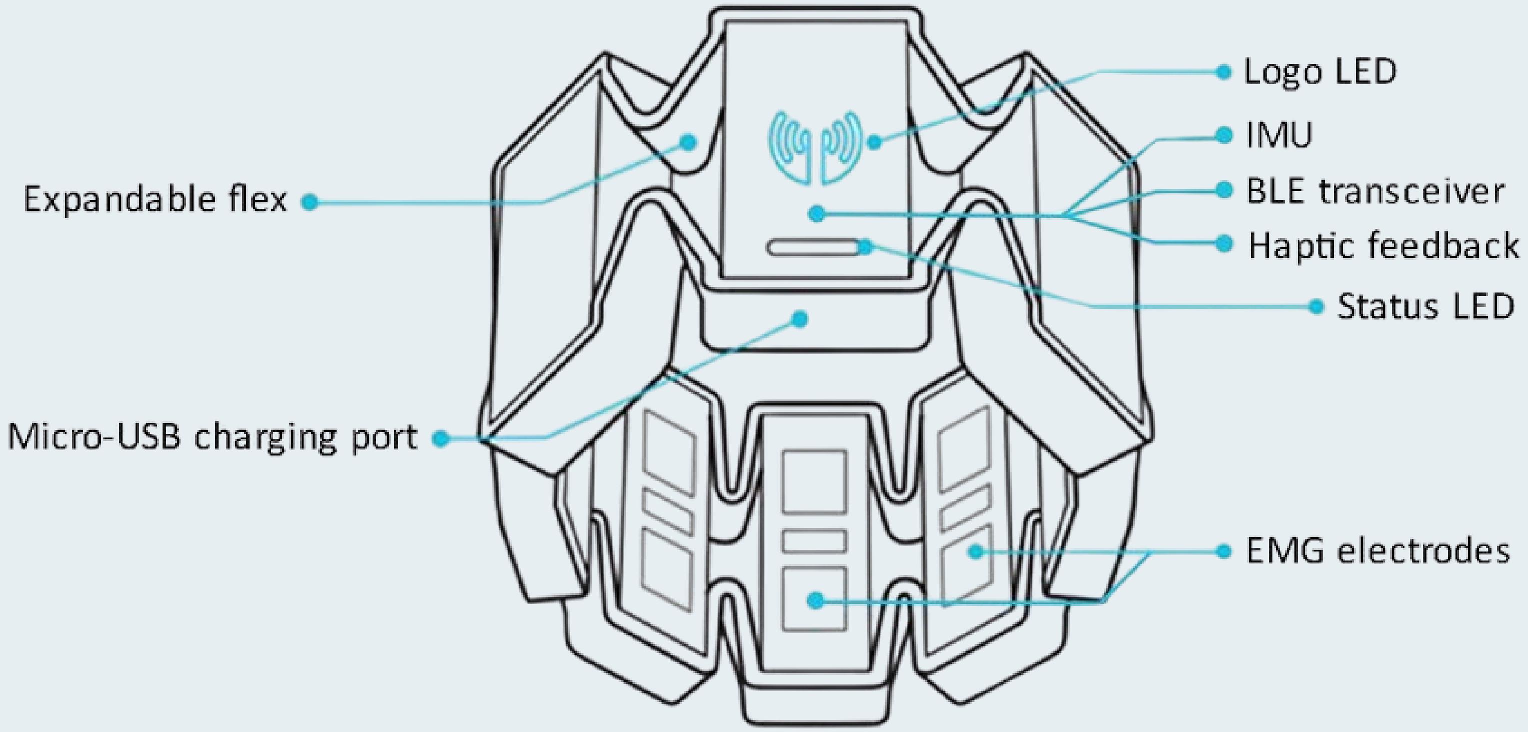
Artificial Intelligence in Biomedical Engineering

Myo

THALMICLABS™



Eight sensors equally spaced around the forearm simultaneously acquire myographic signals.

UC Irvine
Machine Learning
Repository

Time-series

Data Characteristics

36

(Two series each)

Patients

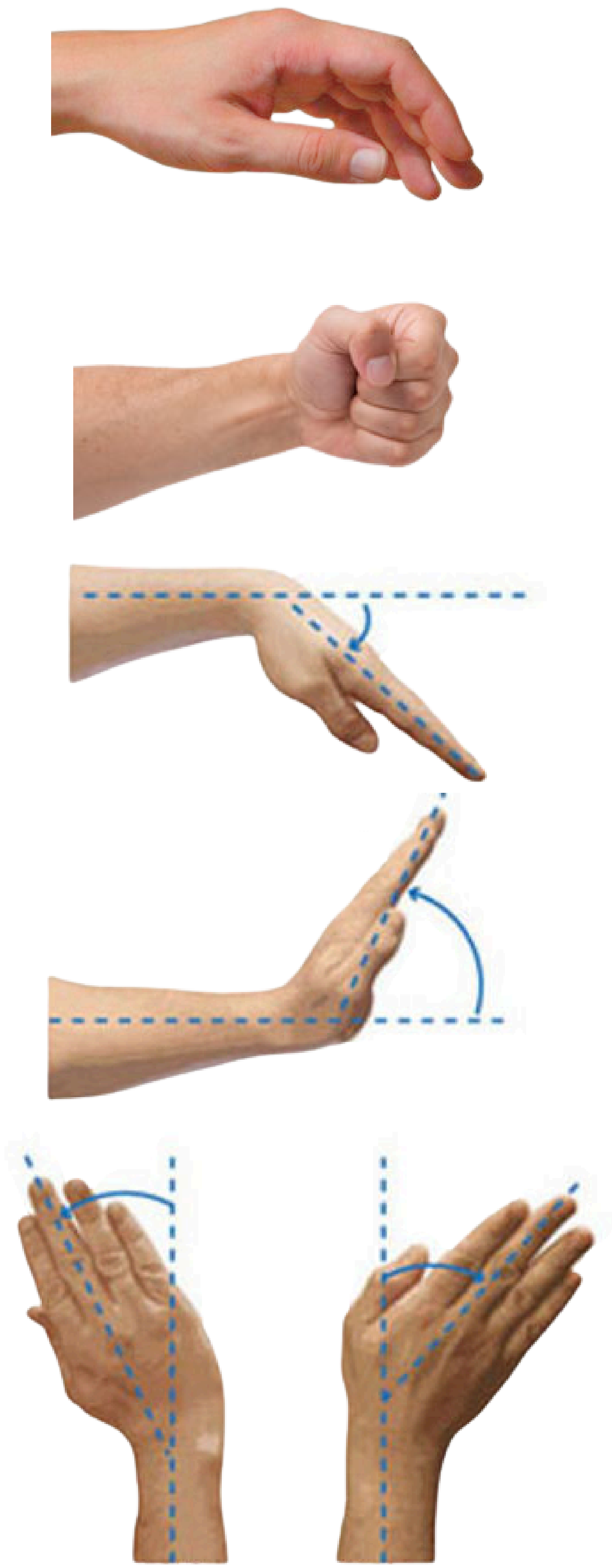
(1.132.344, 11)

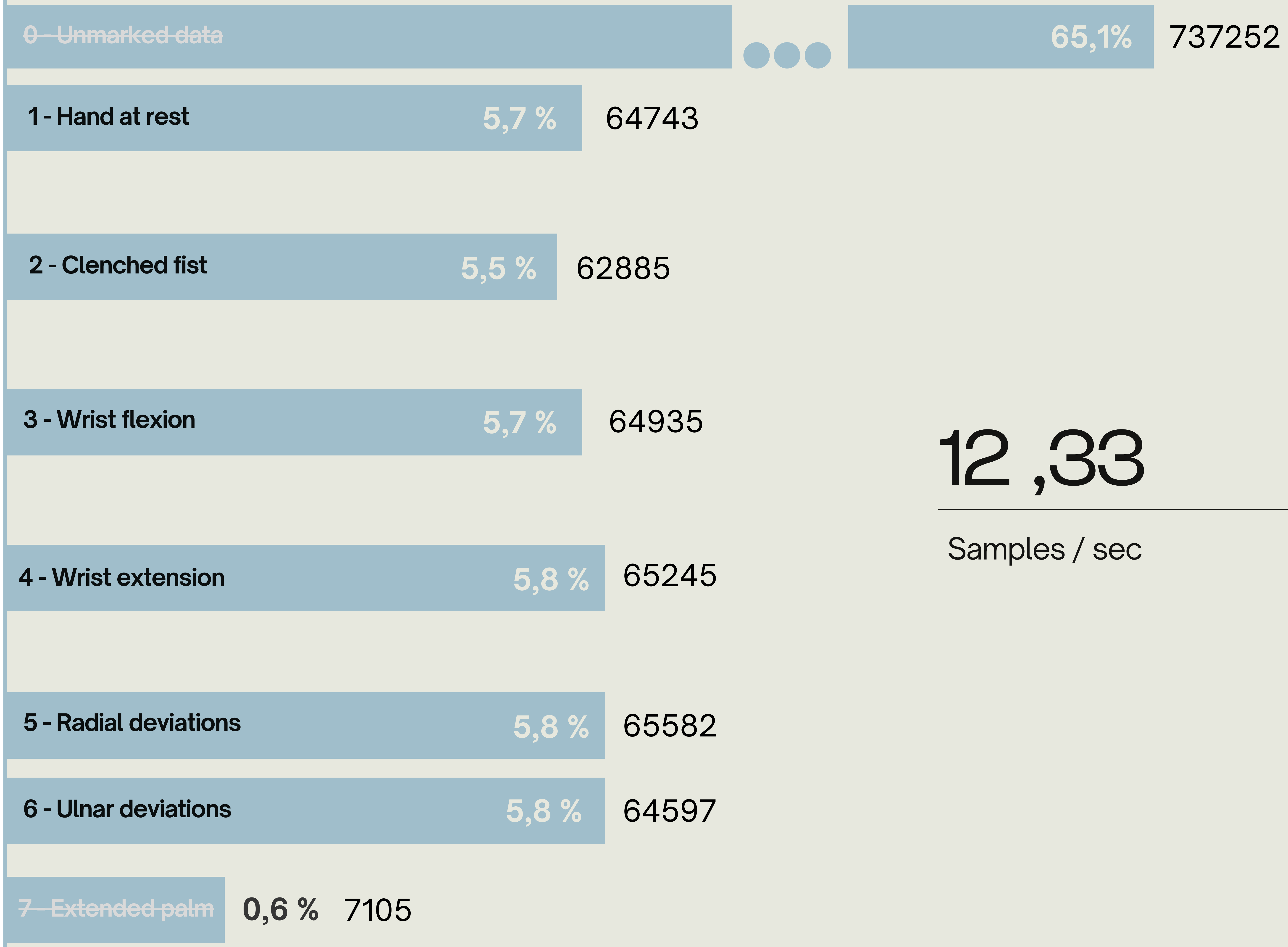
(Rows, Columns)

Combined shape

1 Serie
6 (7) Gestures
3 seconds / gesture
3 seconds pauses

RAW EMG data

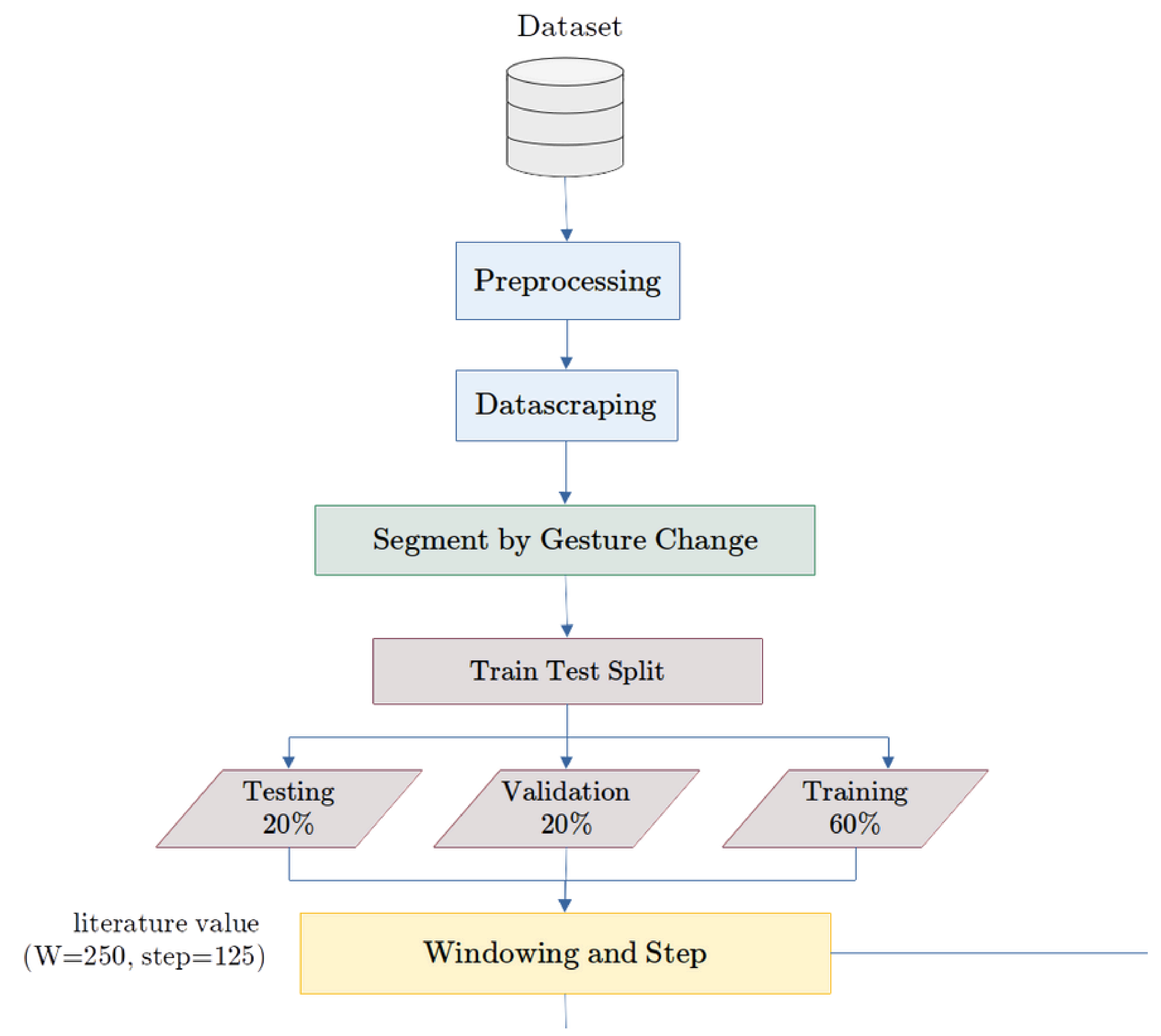




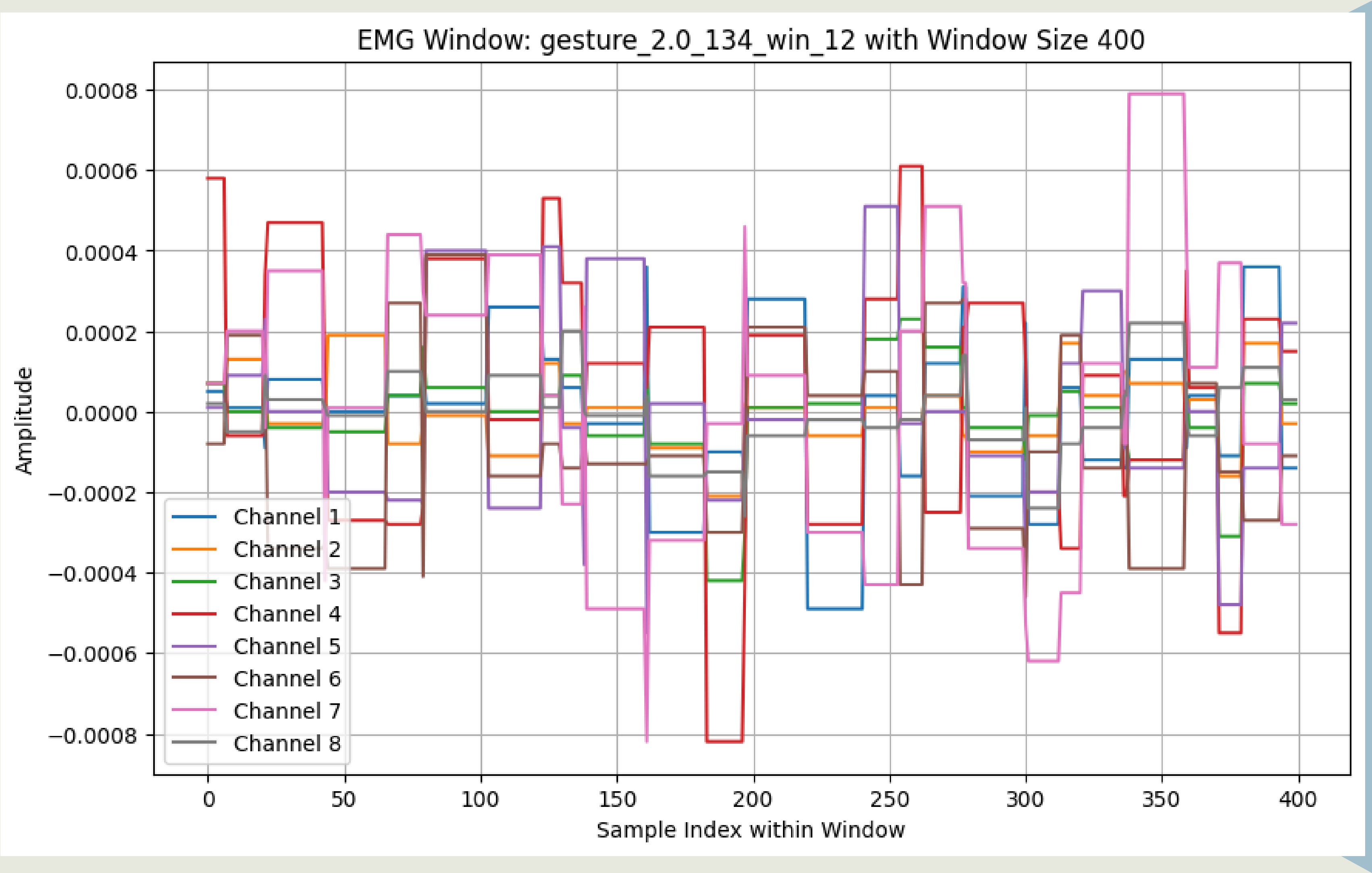
12 ,33

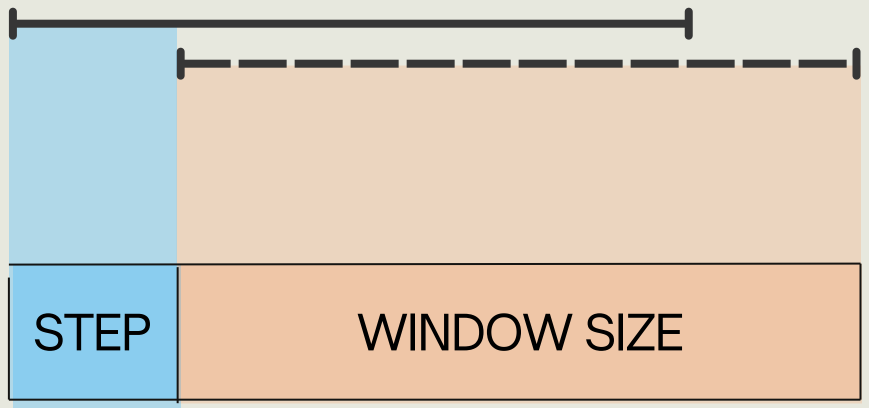
Samples / sec

DATA EXPLORATION

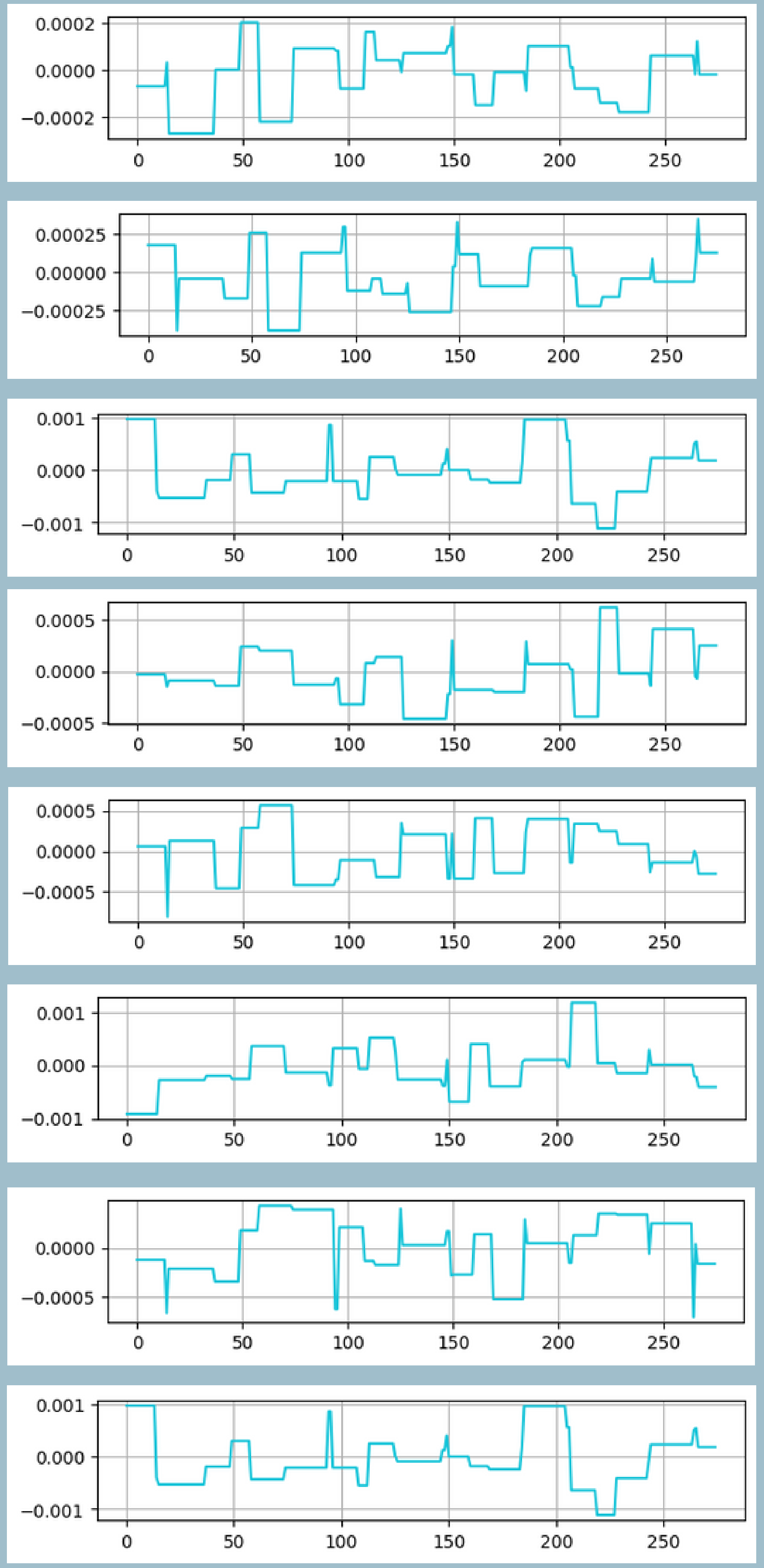


2 - Clenched fist

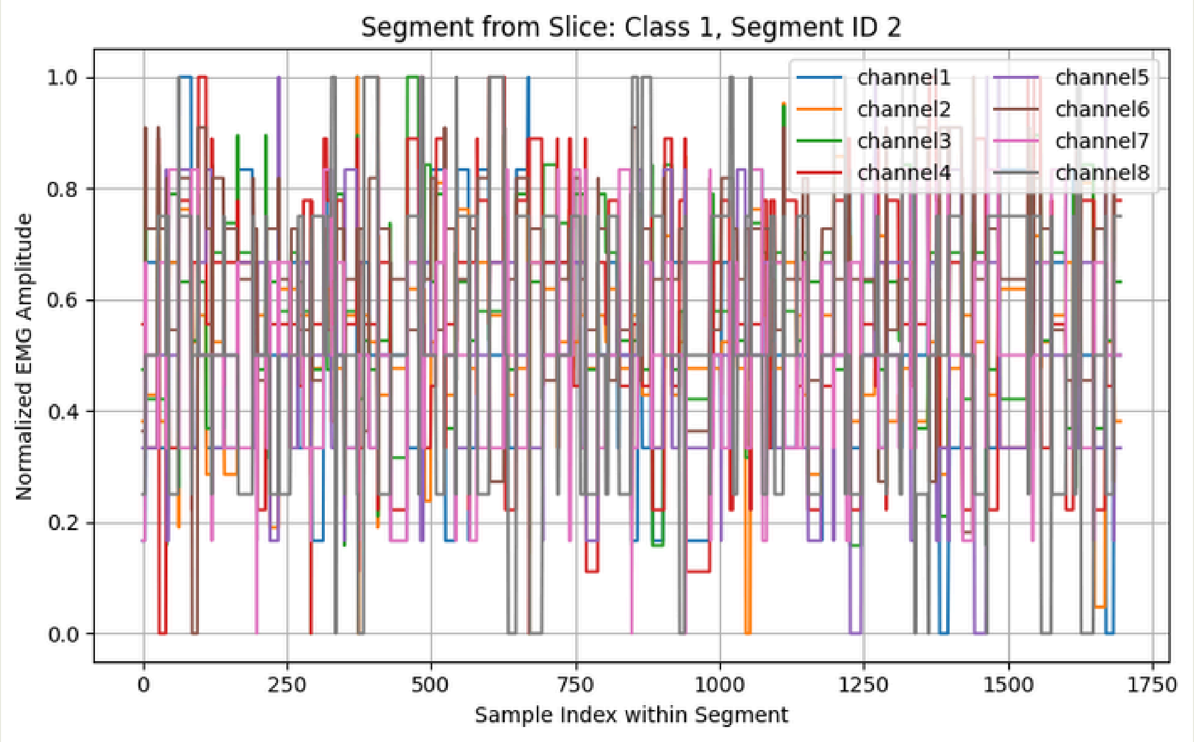




Each movement generates 8 signals, one per electrode recording.



SEGMENT CONTINUOUS
RECORDINGS INTO
GESTURE RUNS



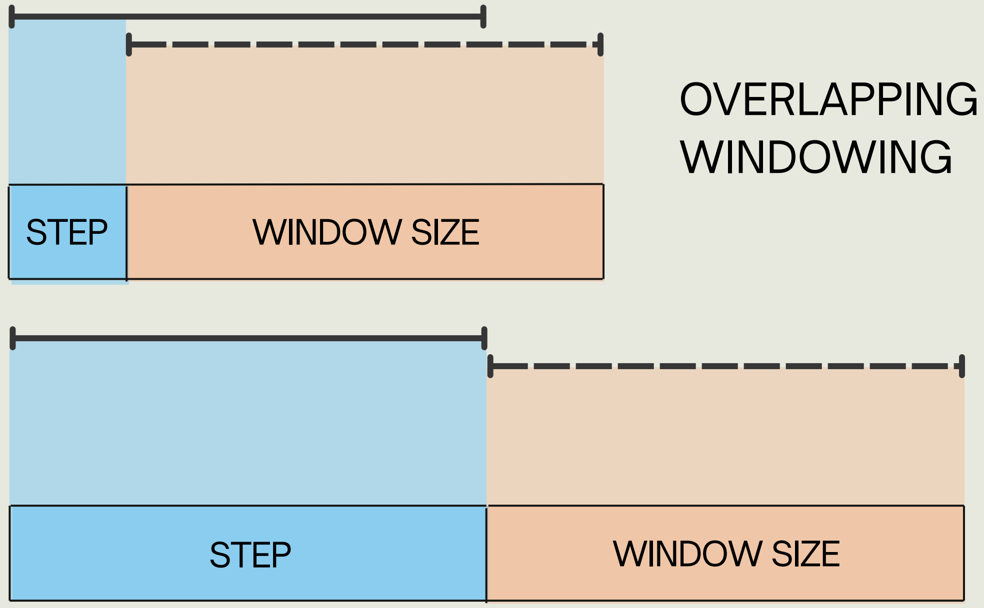
SPLIT SEGMENTS

(STRATIFIED)

60% TRAINING SET

20% TEST SET

20% VALIDATION SET

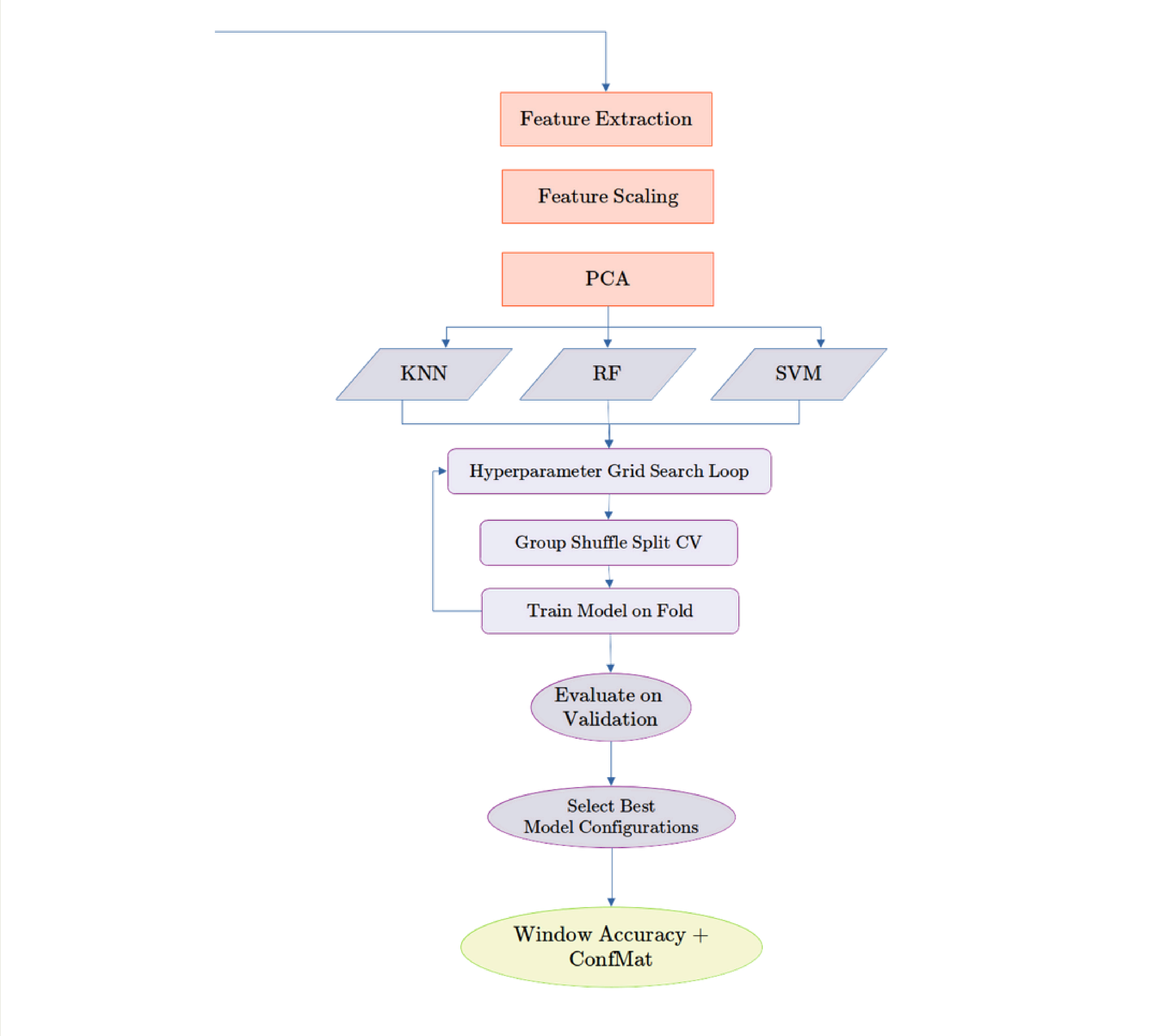


OVERLAPPING
WINDOWING

AVOID DATA
LEAKAGE

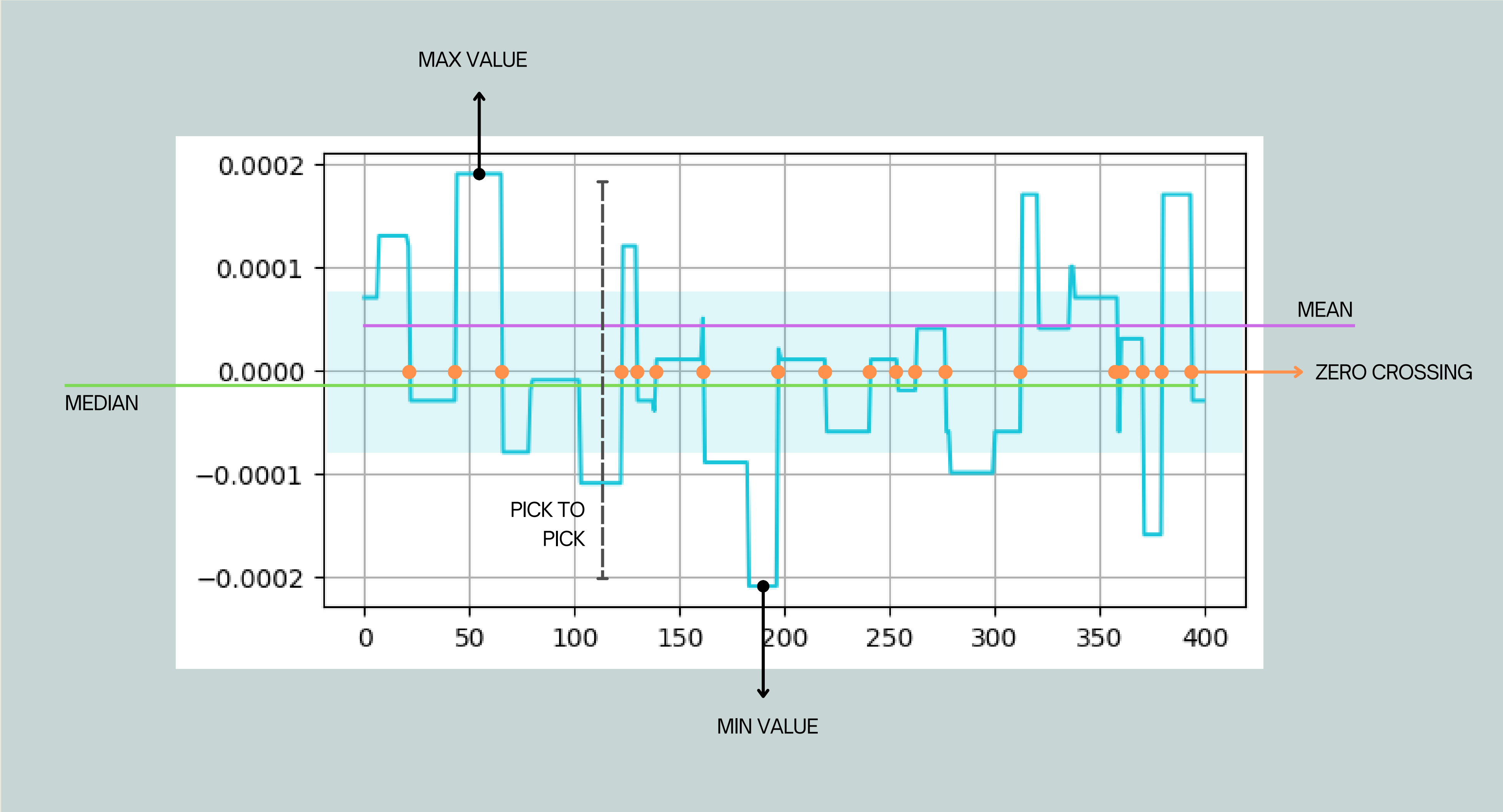
NO OVERLAPPING
WINDOWING

MACHINE LEARNING APPROACH



MACHINE LEARNING
FEATURE EXTRACTION

MEAN	
STD	
MIN	
MAX	
MEDIAN	
MIN DIFF	
STD DIFF	
RMS	
ENERGY	
WAVEFORM LENGTH	
SKEWNESS	
KURTOSIS	
ZERO CROSSING	
SLOPE SIGN CHANGES	



From each window, compute 14 statistical features × 8 channels = 112 features/window.

Dimensionality reduction → PCA

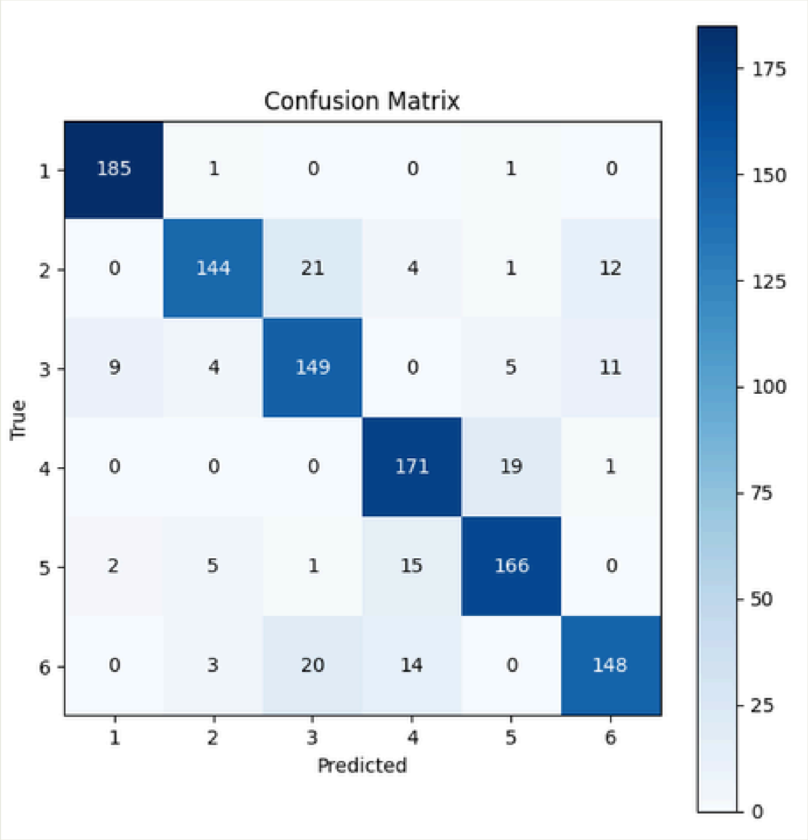
Keep only the components that explain 90% of the total variance

MACHINE LEARNING
MODEL PERFORMANCE

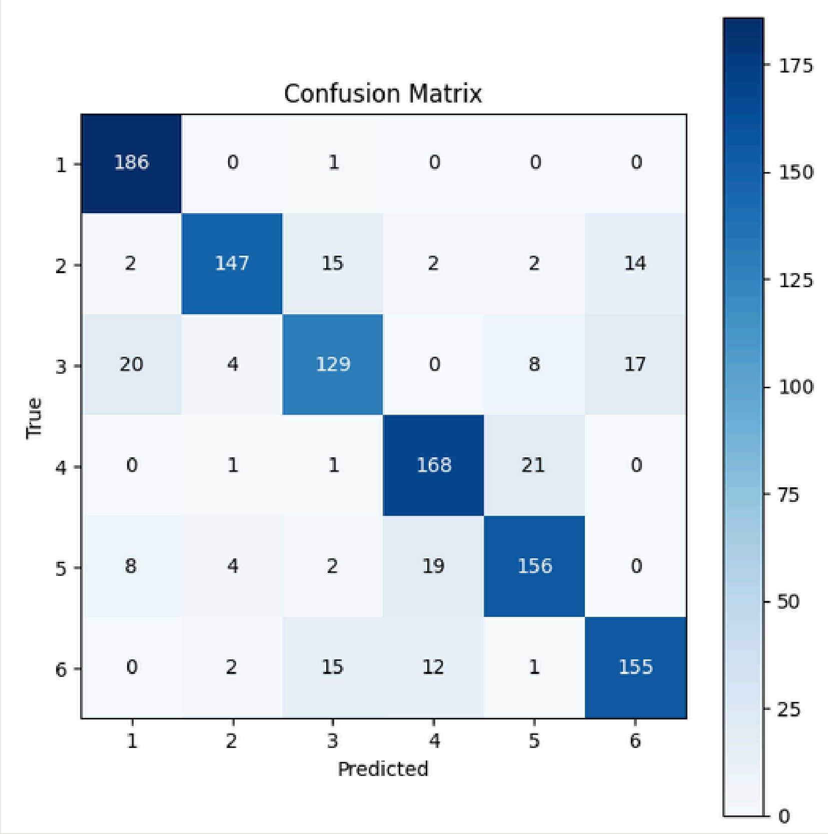
Models tested:

Model	**Tuning Params**
k-NN	n_neighbors = [3, 5, 7, ...]
RF	n_estimators, max_depth, ...
SVM	C, kernel = linear / rbf

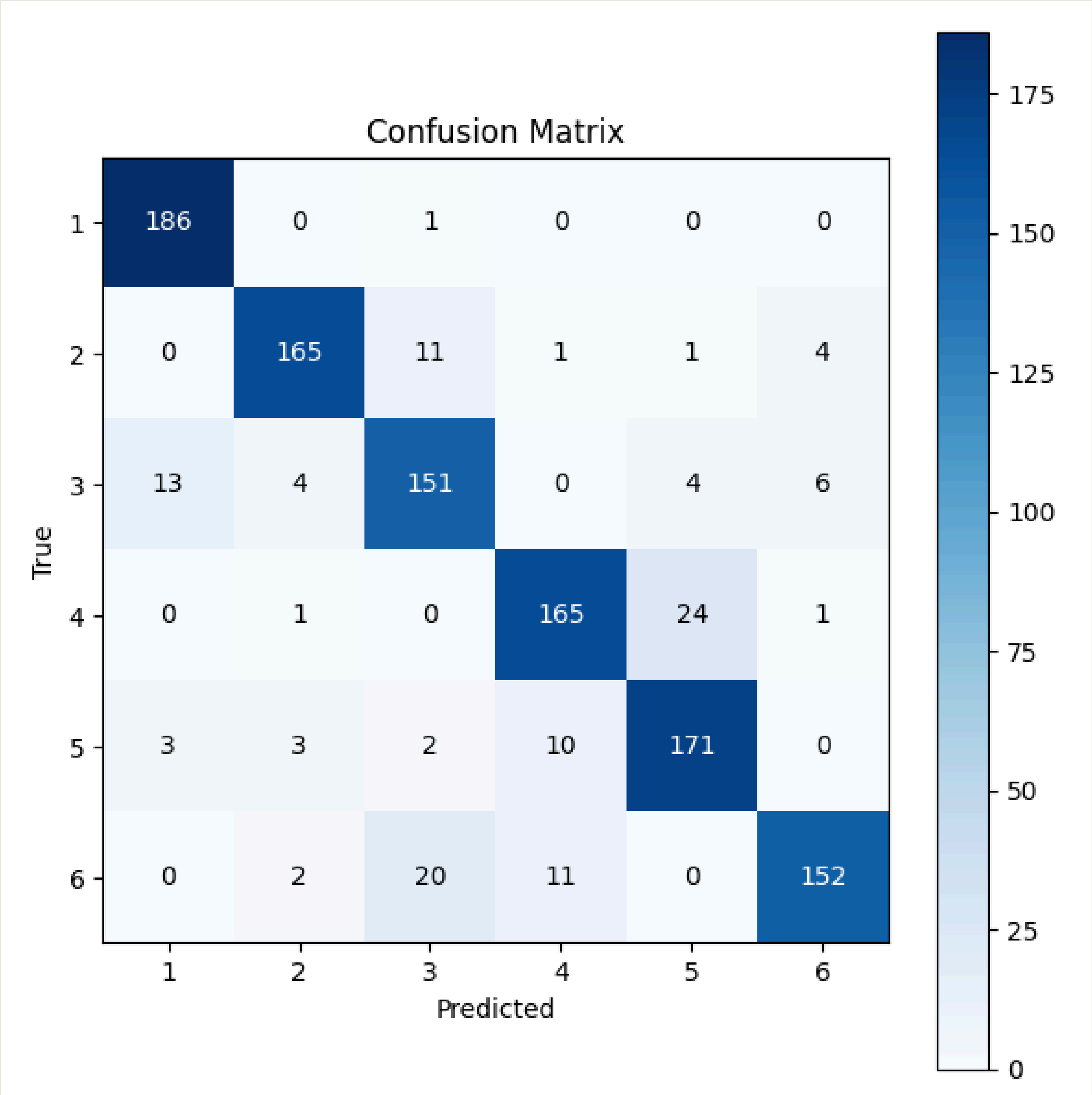
RF



k-NN

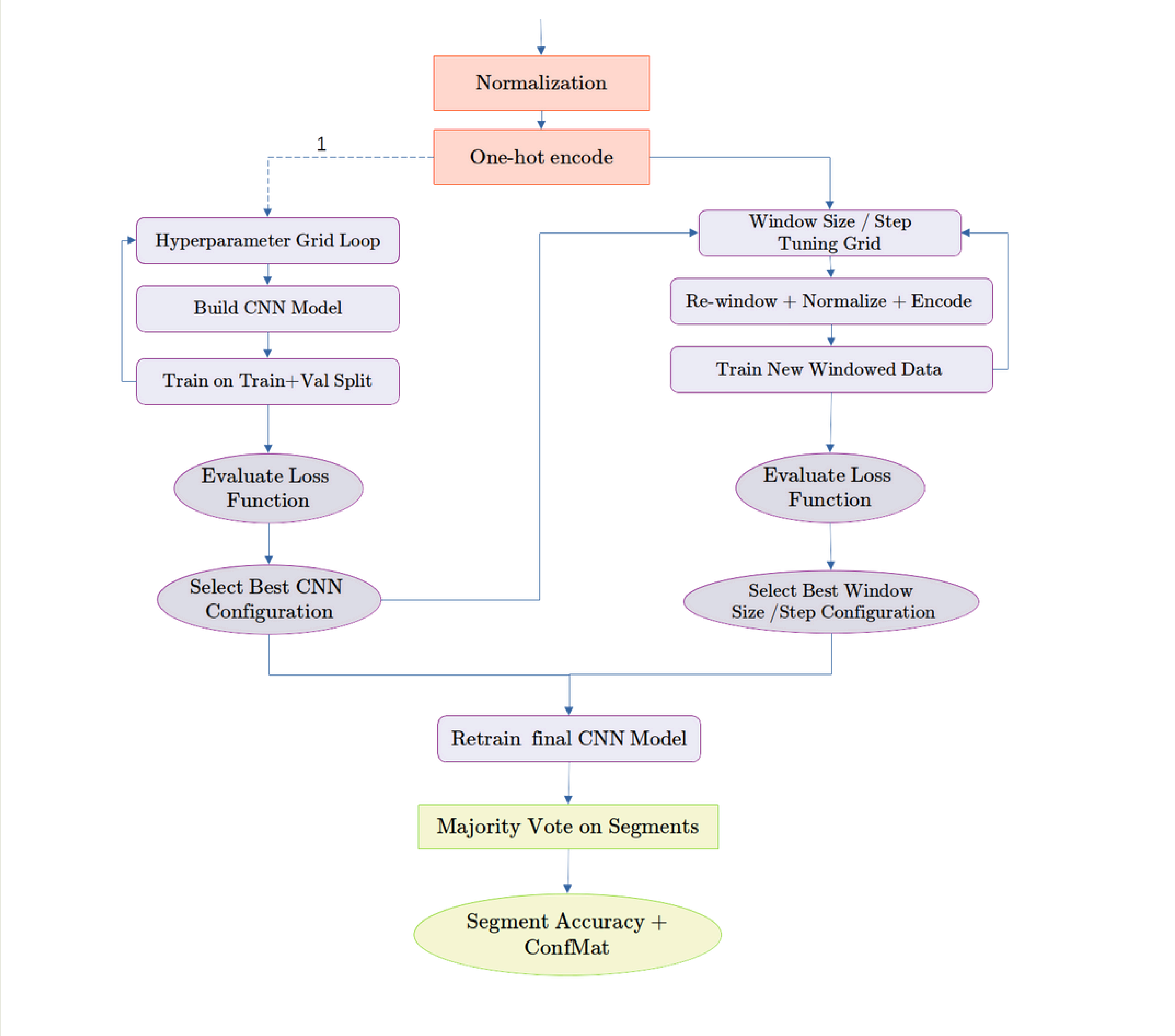


SVM



Accuracy: 0.827

DEEP LEARNING APPROACH



1D CONVOLUTIONAL NEURAL NETWORK

MODEL ARCHITECTURE

Model: "sequential_3"

Layer (type)	Output Shape	Param #
conv1d_9 (Conv1D)	(None, 398, 32)	800
batch_normalization_6 (BatchNormalization)	(None, 398, 32)	128
spatial_dropout1d_3 (SpatialDropout1D)	(None, 398, 32)	0
conv1d_10 (Conv1D)	(None, 396, 32)	3,104
batch_normalization_7 (BatchNormalization)	(None, 396, 32)	128
max_pooling1d_6 (MaxPooling1D)	(None, 198, 32)	0
dropout_9 (Dropout)	(None, 198, 32)	0
conv1d_11 (Conv1D)	(None, 196, 64)	6,208
max_pooling1d_7 (MaxPooling1D)	(None, 98, 64)	0
dropout_10 (Dropout)	(None, 98, 64)	0
flatten_3 (Flatten)	(None, 6272)	0
dense_6 (Dense)	(None, 64)	401,472
dropout_11 (Dropout)	(None, 64)	0
dense_7 (Dense)	(None, 6)	390

1D Convolutions capture temporal EMG patterns.

BatchNorm + Dropout for stable and regularized training.

MaxPooling reduces sequence length, keeps key features.

Dense + Softmax layers classify gestures from learned features.

MODEL TUNING TO ADAPT ARCHITECTURE TO EMG STRUCTURE

CNN architecture grid search

Hyperparameter	Values
Filters	16, 32
Kernel Size	3, 5
Dropout Rate	0.2, 0.4
Dense Units	64, 128
Weight Decay	1e-4, 1e-3
Learning Rate	1e-3, 5e-4

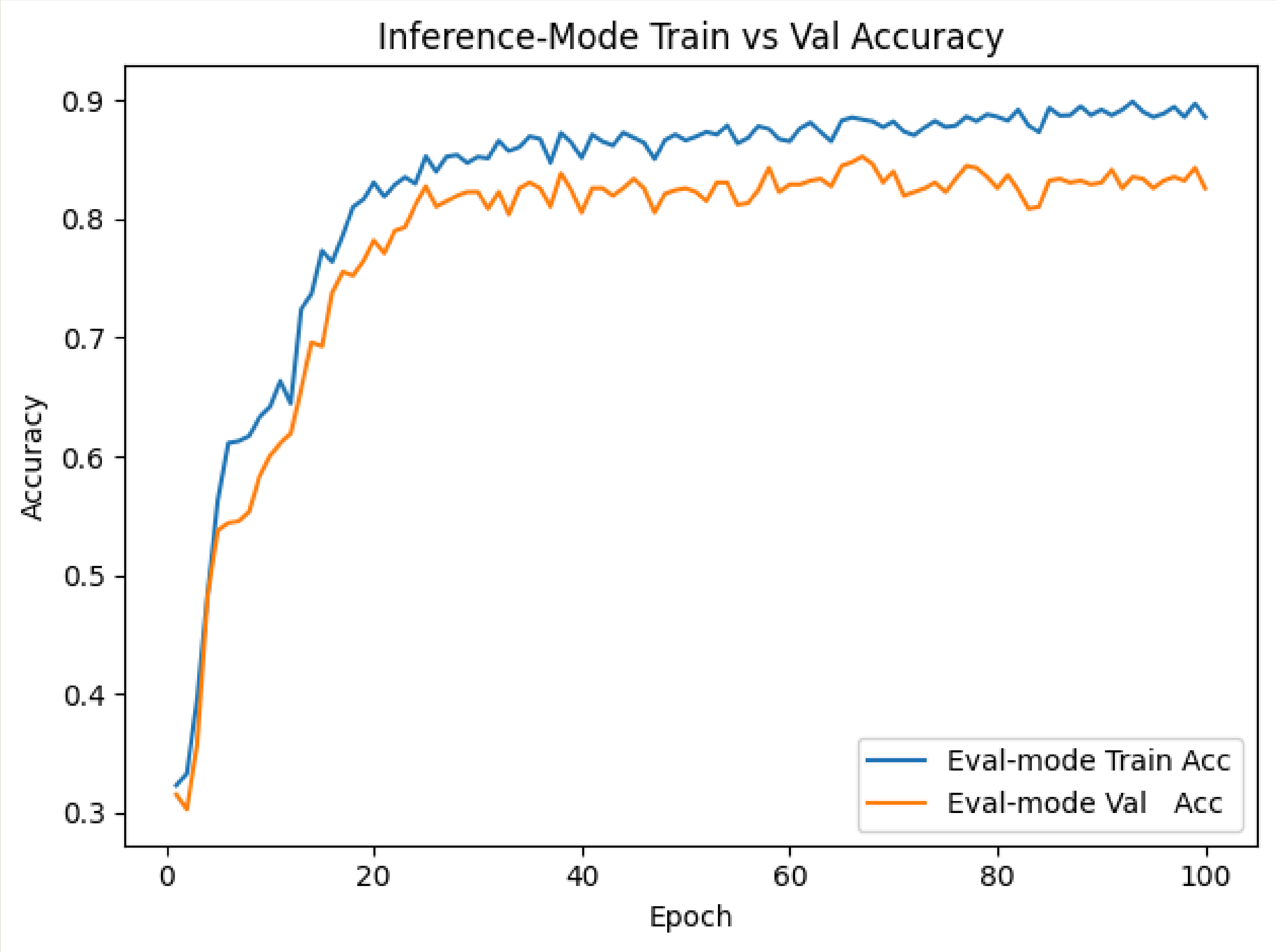
SEGMENTATION TUNING IMPROVES DATA REPRESENTATION

Window size and step size grid search

Window Size	Step Size
250	100, 175, 250
400	100, 175, 250
500	100, 175, 250

1D CONVOLUTIONAL NEURAL NETWORK

FINDING THE BEST CONFIGURATION



Filters	Kernel Size	Dropout Rate	Weight Decay	Dense Units	Learning Rate	Window Size	Step Size
32	3	0.4	0.001	64	0.0005	400	100

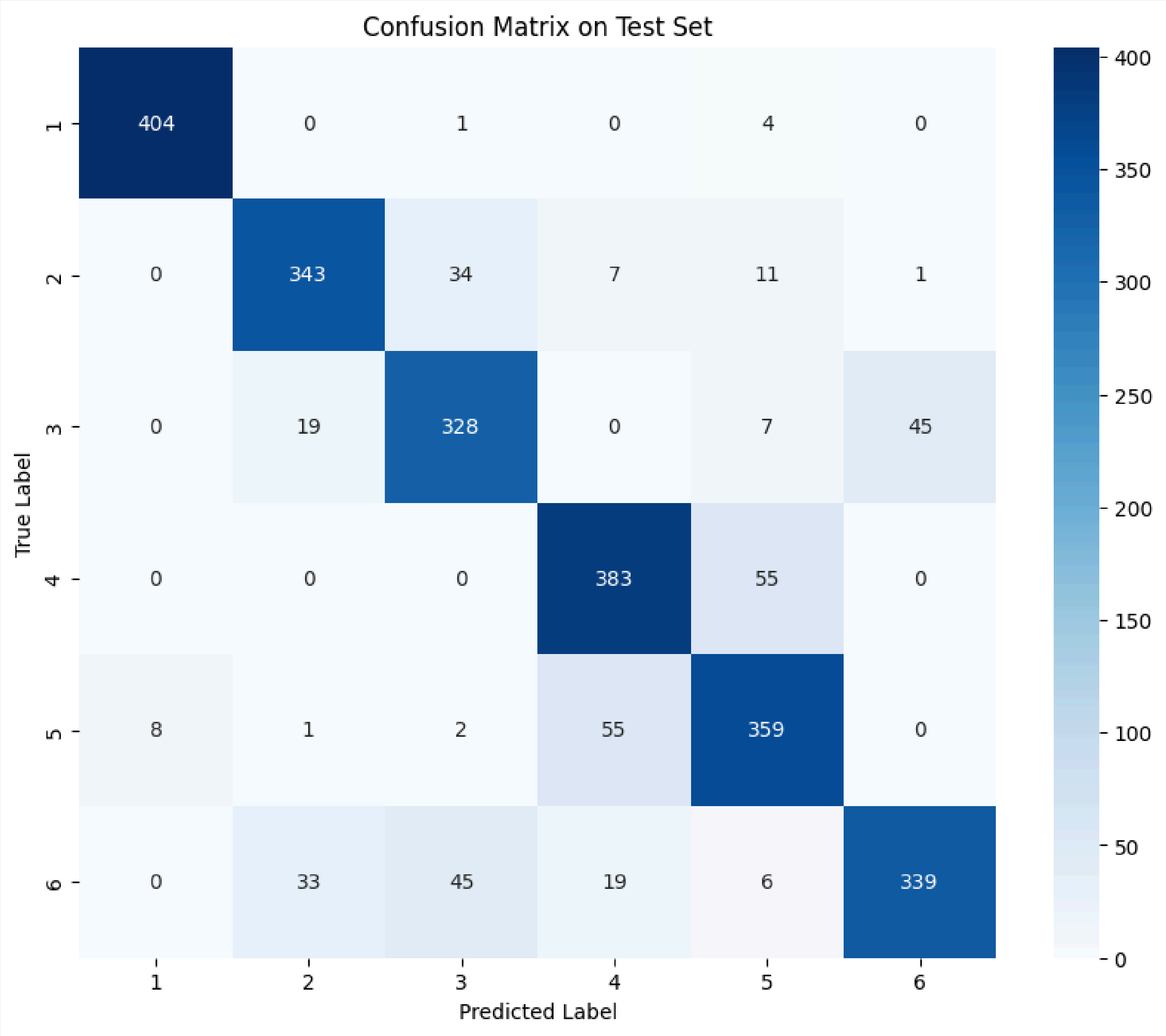
1D CONVOLUTIONAL NEURAL NETWORK

WINDOW LEVEL PERFORMANCE

CLASSIFICATION REPORT:

	PRECISION	RECALL	F1-SCORE	SUPPORT
1	0.98	0.99	0.98	409
2	0.87	0.87	0.87	396
3	0.80	0.82	0.81	399
4	0.83	0.87	0.85	438
5	0.81	0.84	0.83	425
6	0.88	0.77	0.82	442
ACCURACY			0.86	2509
MACRO AVG	0.86	0.86	0.86	2509
WEIGHTED AVG	0.86	0.86	0.86	2509

Each window is classified independently



1D CONVOLUTIONAL NEURAL NETWORK

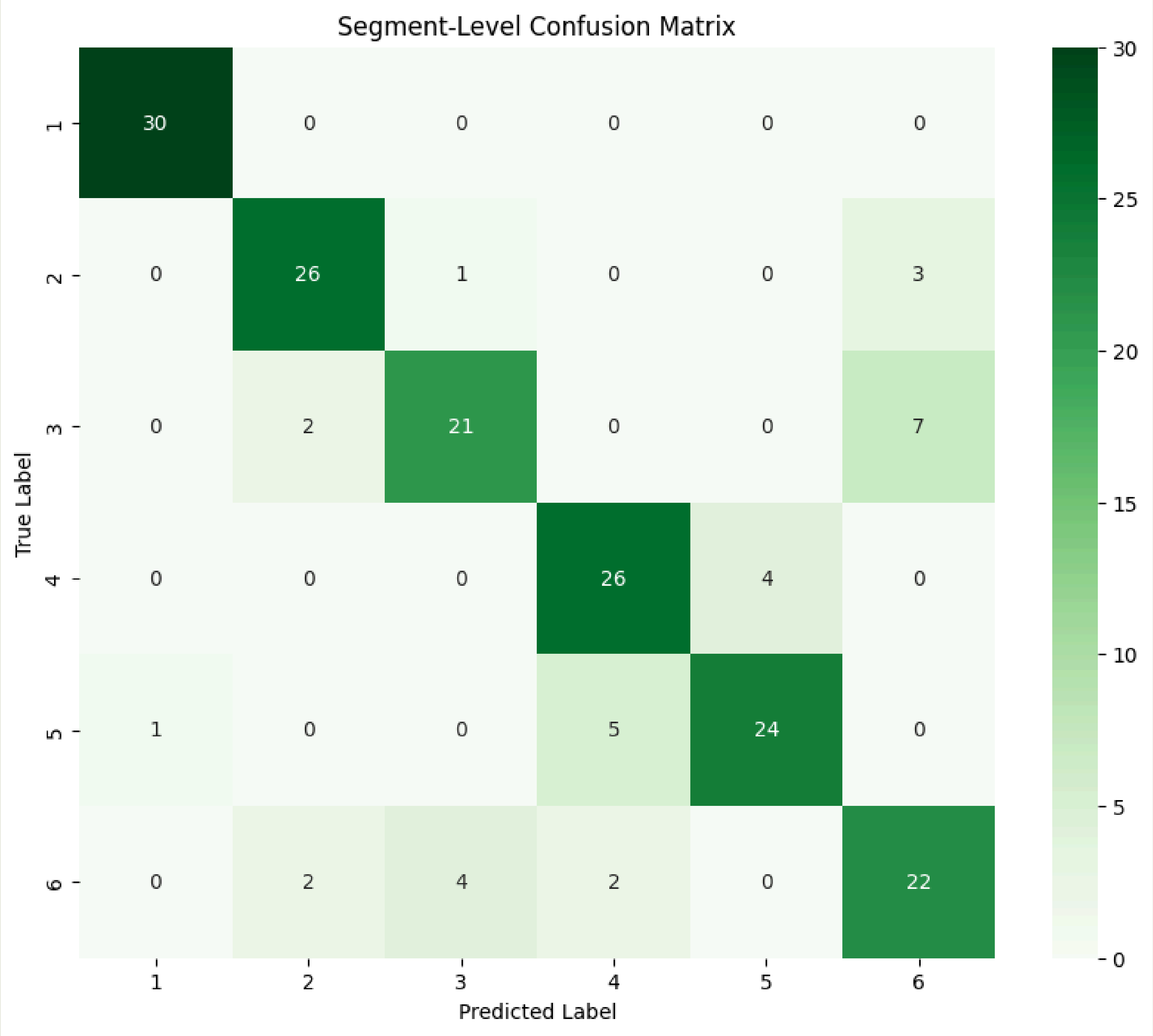
SEGMENT LEVEL PERFORMANCE

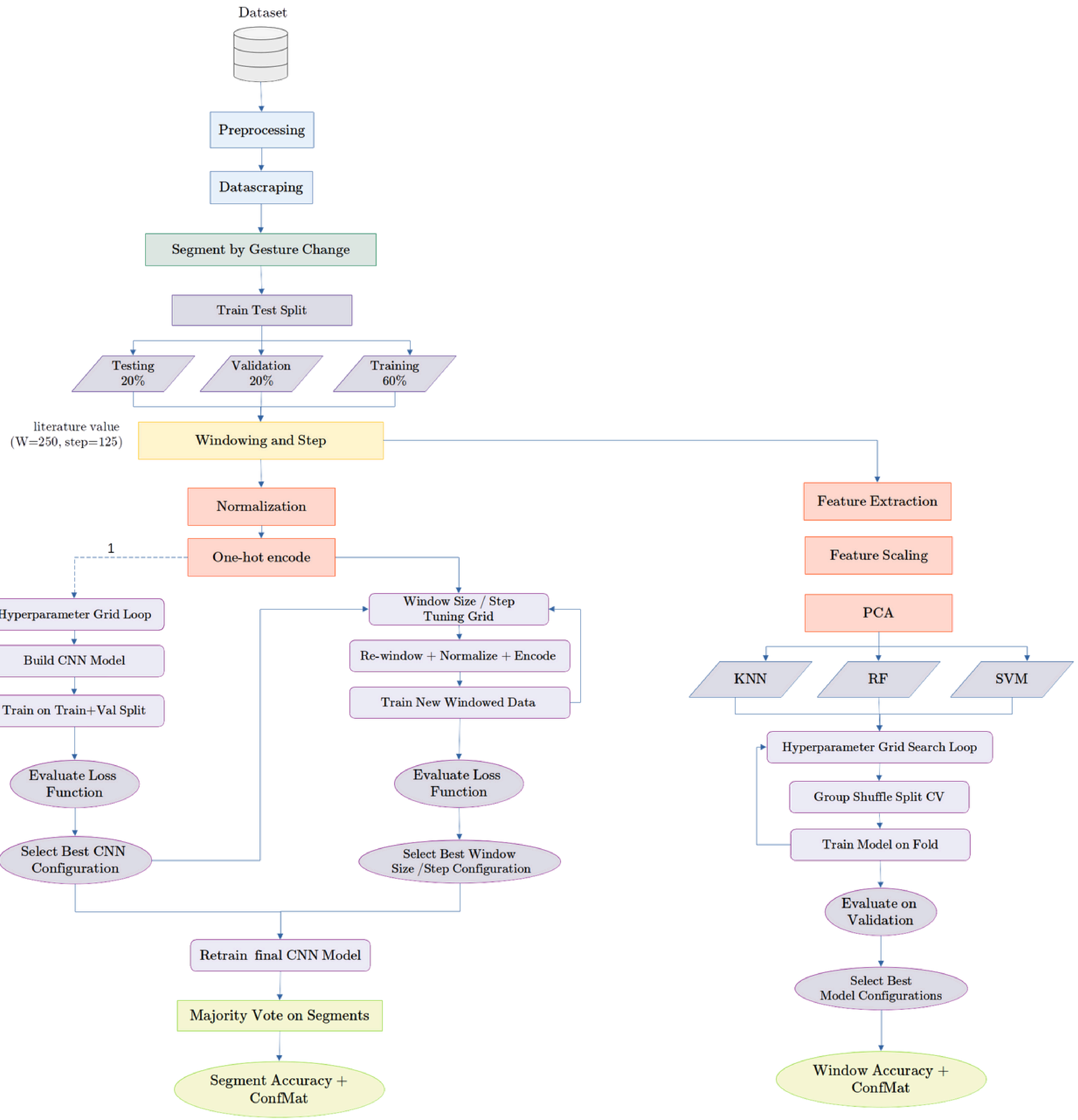
SEGMENT-LEVEL CLASSIFICATION REPORT:

	PRECISION	RECALL	F1-SCORE	SUPPORT
1	0.97	1.00	0.98	30
2	0.87	0.87	0.87	30
3	0.81	0.70	0.75	30
4	0.79	0.87	0.83	30
5	0.86	0.80	0.83	30
6	0.69	0.73	0.71	30
ACCURACY			0.83	180
MACRO AVG	0.83	0.83	0.83	180
WEIGHTED AVG	0.83	0.83	0.83	180

Combine predictions for all windows in a segment

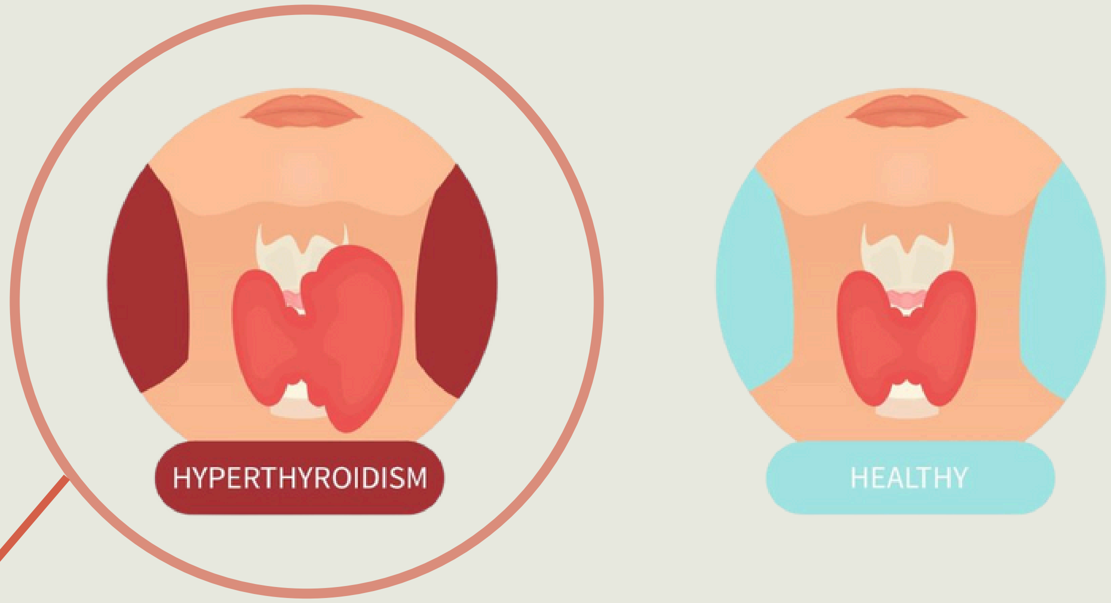
Majority vote





FINAL OVERVIEW

DETECTING FINE TREMORS IN **HYPERTHYROIDISM**



Can cause TREMORS

Hard to see
Vary throughout the day
rarely measured objectively

No standard tool exists to track them in real time

Use our EMG + AI gesture model to:

- Detect fine, involuntary hand tremors
- Measure their frequency and intensity
- Track tremor evolution over time as a proxy for thyroid hormone activity

DETECTING FINE TREMORS IN **HYPERTHYROIDISM**

ETHICAL CONSIDERATIONS INTEGRATED IN THE PROJECT

- Using GroupShuffleSplit to force generalization and not memorization of each person pattern
- The system is design to assist clinicians, by providing objective, data-driven insights.

FURTHER BIAS CONSIDERATIONS

- Ensure diversity in the patient's dataset

SUSTEINABILITY CONSIDERATIONS

- The system operates with low energy consumption.

- The data used from training can be reused from other projects.

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