Development of a Deep Learning Algorithm using Electromyography (EMG) and Acceleration to Monitor Upper Extremity Behavior with Application to Individuals Post-Stroke

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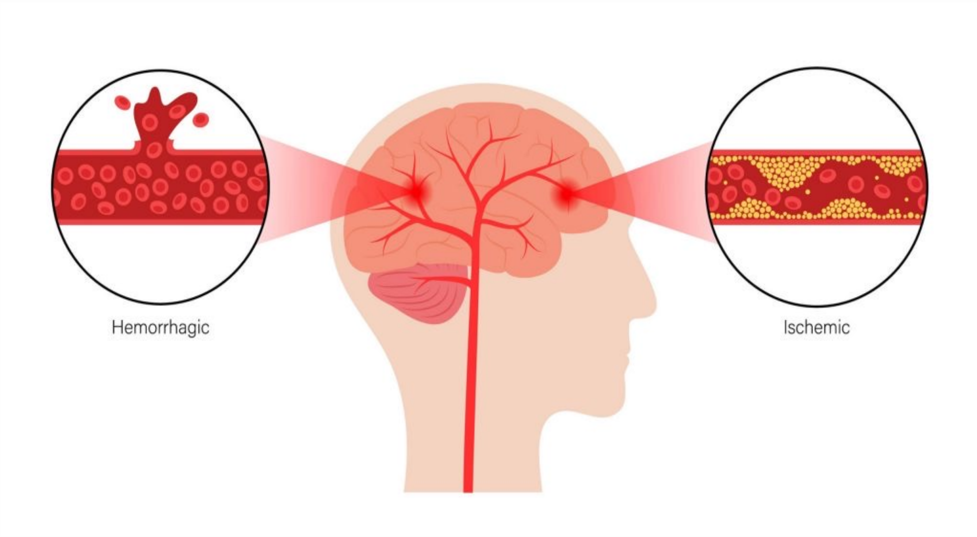
Background

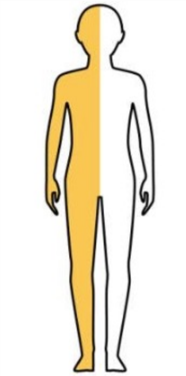
Stroke

- Blood supply to the brain is interrupted
- Permanent brain damage
- Impaired cognitive abilities, speech, and motor function



Recovery

- Hemiparesis is characterized as weakness or partial paralysis of one side of the body [12]
- https://www.youtube.com/watch?v=SlJk88Nd-ZM



80%
Upper extremity impairment [14]

20%
No functional arm usage

5%
Regain full arm usage

800,000

Stroke patients per year in U.S [2]

19%

Percentage of strokes in people who have previously had a stroke

$59,000

Cost per patient per year [5]

Current Stroke Care

Stroke	Hospitalization	Inpatient Therapy	Outpatient Therapy
01	02	03	04
Patient is rushed to hospital, intervention takes place	Patient under continuous monitoring, stabilization	Basic motor recovery exercises, strengthening	Patient moves to home setting, 1-2x weekly therapy

Timeline

Current Stroke Care

Outpatient Therapy

04

- Disproportionate amount of time spent in this stage of rehabilitation
- Limited in time and medical insurance coverage
- Providers typically reduce sessions/week after 1 month, stop altogether as early as 6 months - 1 year [9-11]

Improvement in physical therapy ≠ improvement in functional, at-home arm use

Recovery

- Activities of Daily Living (ADL) are commonly used metric to assess functional independence of post-stroke individuals [15-17]
- Performance of ADLs in home-setting correspond to improved motor recovery outcomes [19,20]

02

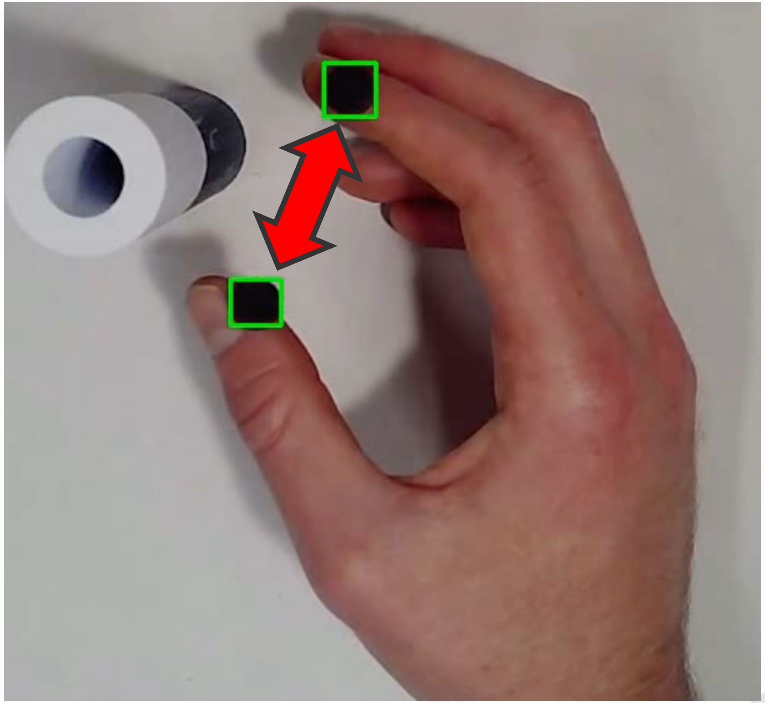
Predicting Grip Aperture using Muscle Activation Data: Background

Recovery

- Activities of Daily Living (ADL) are commonly used metric to assess functional independence
- Performance of ADLs in home-setting correspond to improved motor recovery outcomes
- Reach-to-grasp (RTG) often requires compensatory movements [17,18]

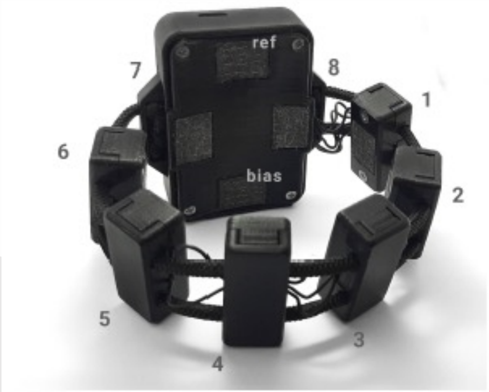
Recovery

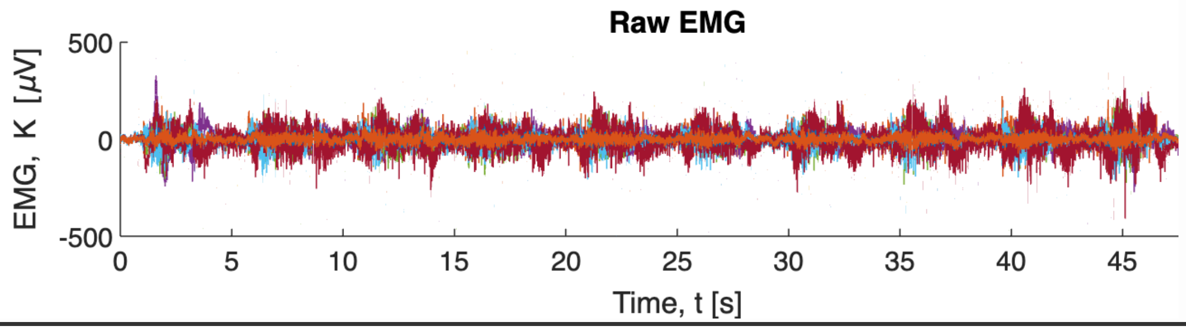
- A metric further tied to RTG success is grip aperture [21, 22]
- Characterization of aperture can help quantify RTG performance in the home setting



Electromyography(EMG)

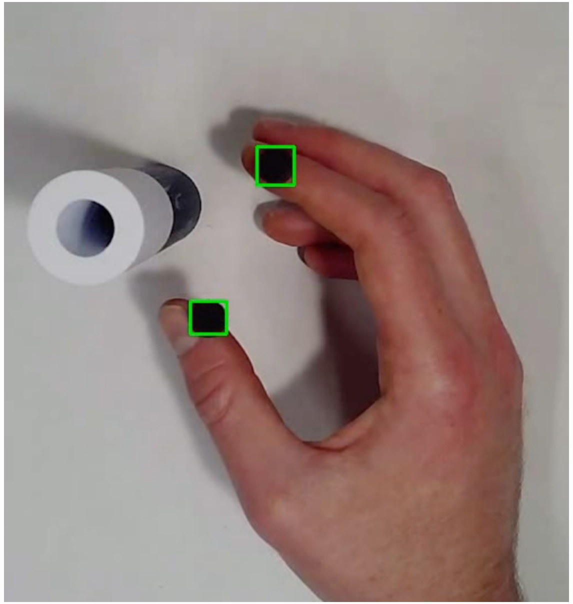
- Measures nerve electrical activity in response to muscle activation
- Measurement systems can be either surface (seen below), or needle-based
- Novel armband provides a lightweight, non-invasive medium

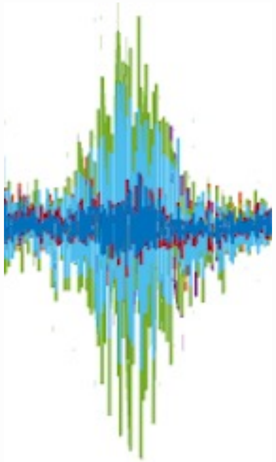




Contribution 1

Can a relationship between grip aperture and EMG be established, with the long-term goal of developing real-time monitoring and assessment tools?

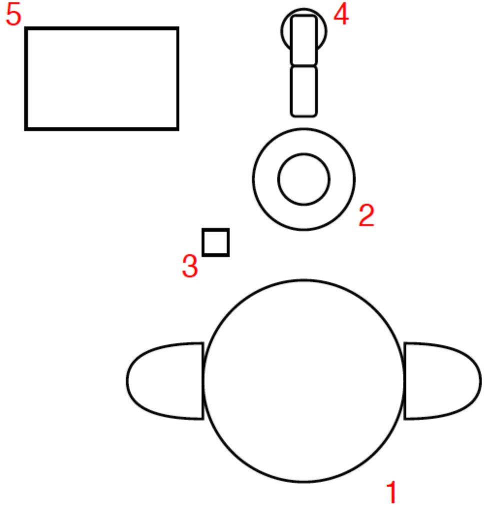




03

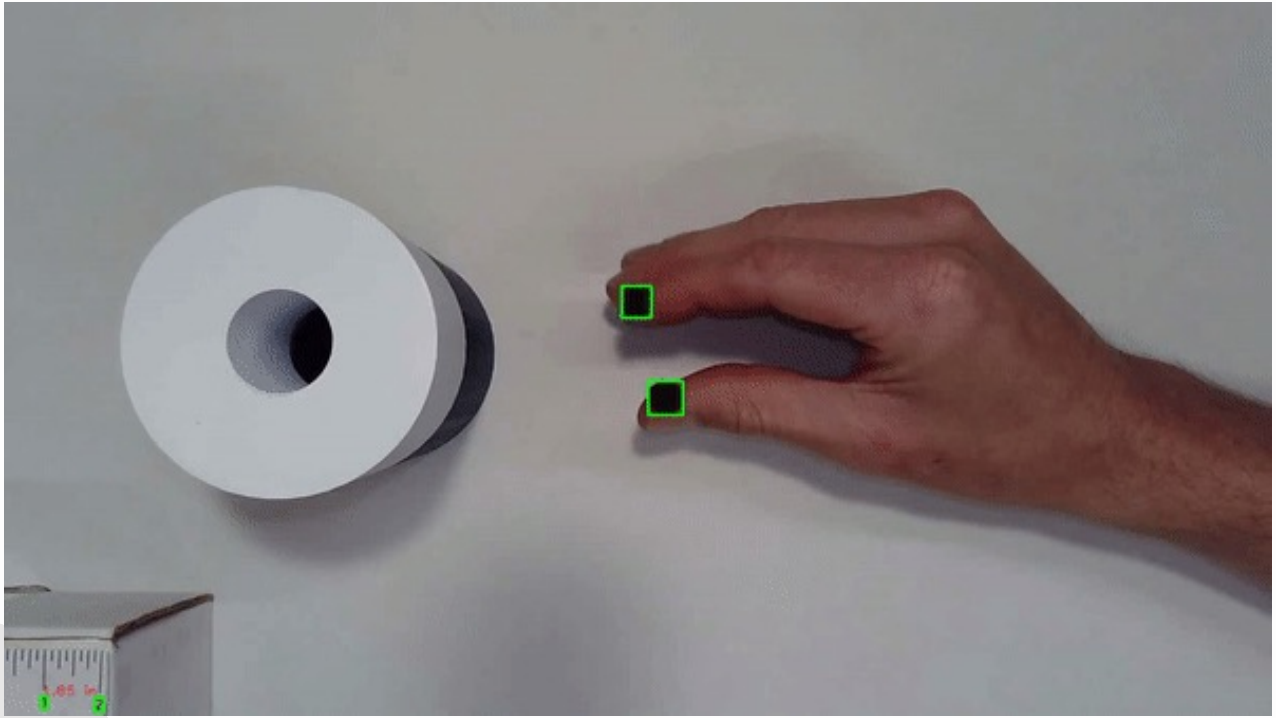
Predicting Grip Aperture using Muscle Activation Data

Methods – Test Bench

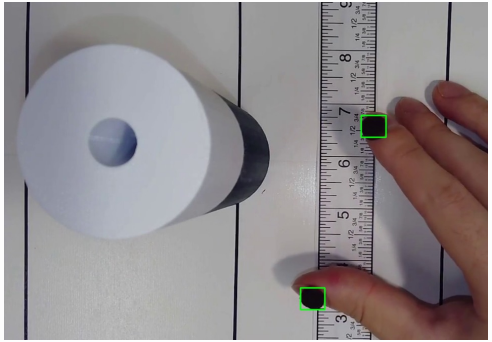


Item #	Description
1	Participant
2	Cylinder simulating grasp
3	Ruler
4	Document camera
5	Laptop collecting data

Methods – Computer Vision Application

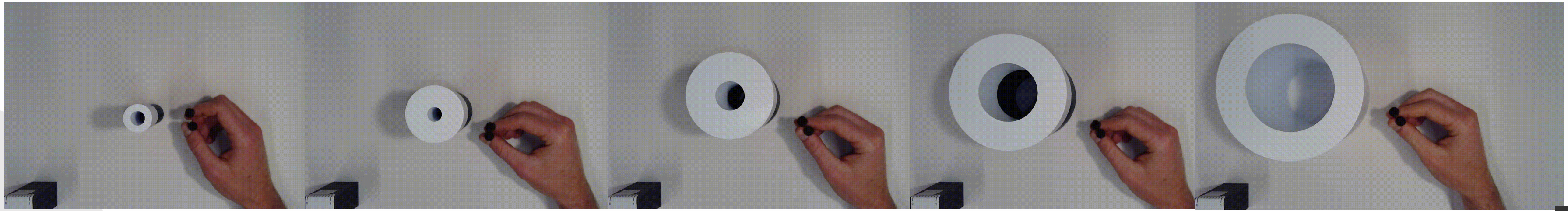


- Most accurately simulates grasping motion



Methods – Procedure

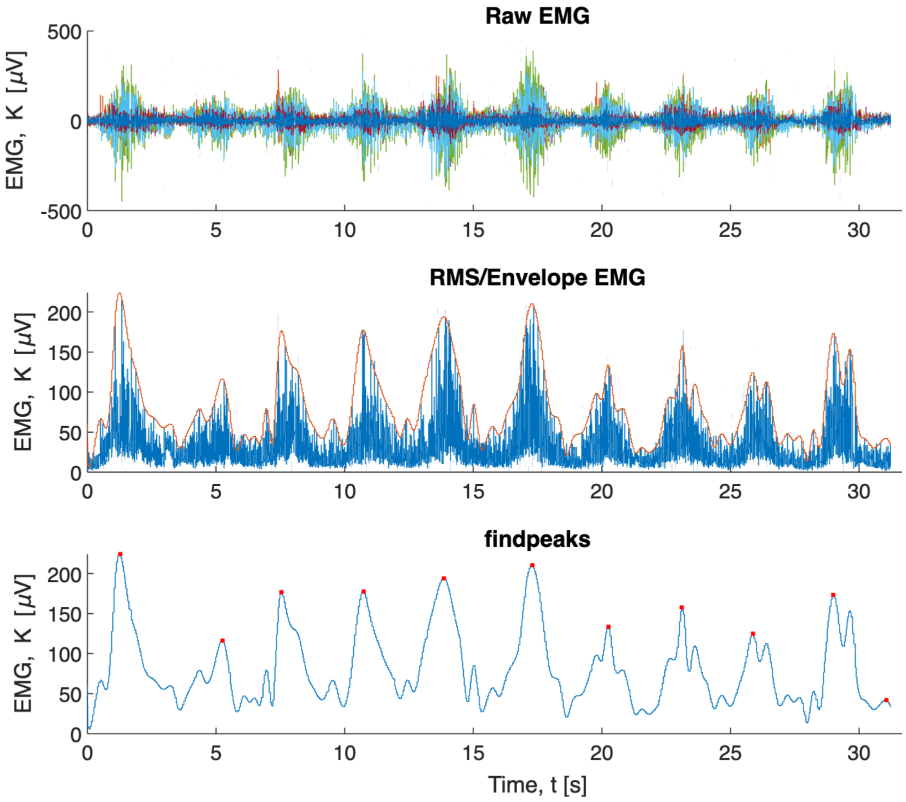
- 10 non-disabled, male participants recruited
- 5 cylinders of increasing radii
- 10 repetitions of grasping motion per cylinder



Methods – Data Processing

$$f_{RMS} = \sqrt{\frac{1}{n}\left(x_1^2 + x_2^2 + \ldots + x_n^2\right)}$$

- Data processing conducted in MATLAB environment
- Utilized *envelope* command to reduce noise
- *Findpeaks* command to find peak locations



Methods – Data Analysis

Individual Data

- Correlation analysis between true aperture and peak EMG

    - Non-parametric Spearman's rank correlation

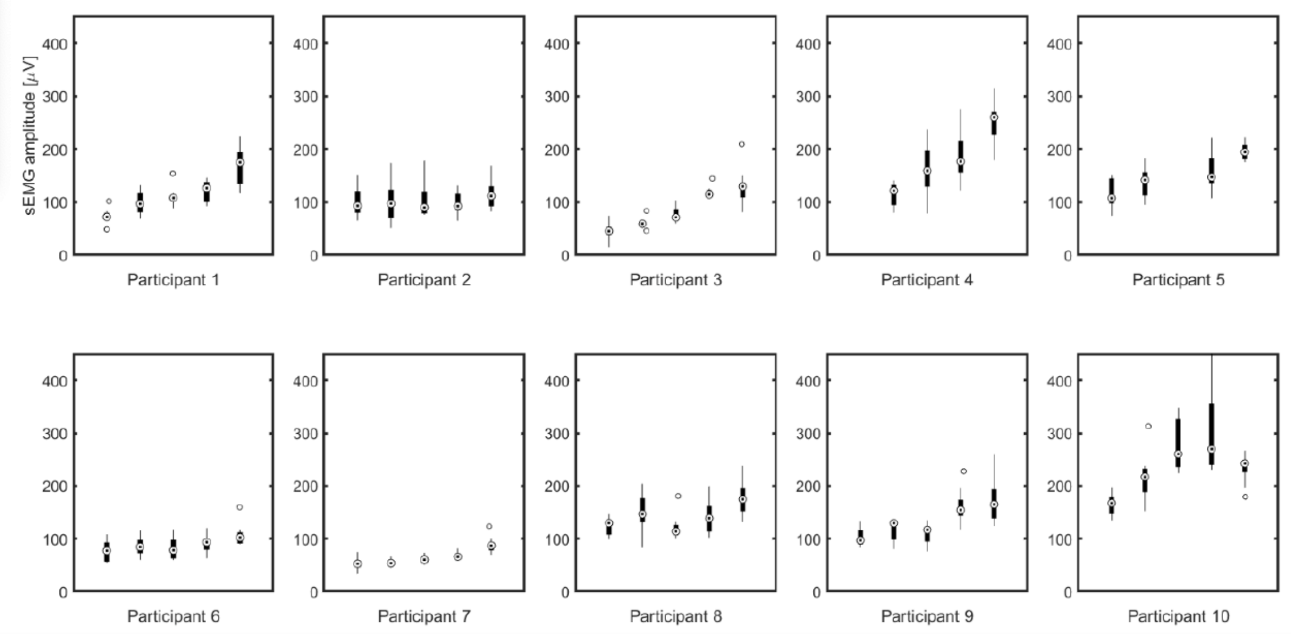
Group Data

- Statistical analysis between cylinder diameter and EMG

    - Non-parametric Friedman Test

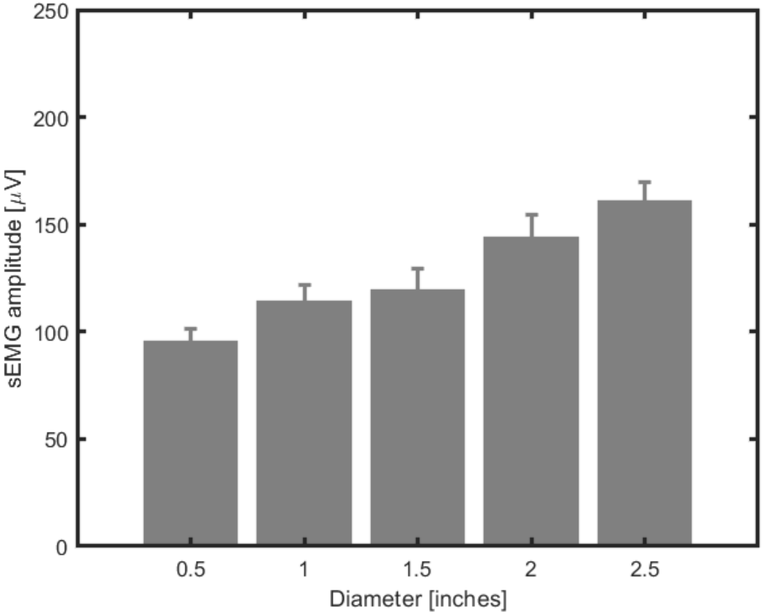
- Significance level $\alpha = 0.05$, Bonferroni corrections applied
- All tests performed in SPSS

Results – Individual Participant



Participant ID	Spearman's ρ	p-value
1	0.758	<0.001
2	0.208	0.152
3	0.883	<0.001
4	0.660	<0.001
5	0.700	<0.001
6	0.408	0.004
7	0.801	<0.001
8	0.304	0.033
9	0.746	<0.001
10	0.604	< 0.001

Results – Group Data



Diameter Relationship	Test Statistic, Z	p-value
D1 - D2	-3.563	<0.001
D1 - D3	-3.582	<0.001
D1 - D4	-5.722	<0.001
D1 - D5	-7.052	<0.001
D2 - D3	-2.361	0.018
D2 - D4	-5.111	<0.001
D2 - D5	-6.839	<0.001
D3 - D4	-3.884	<0.001
D3 - D5	-5.914	<0.001
D4 - D5	-4.326	<0.001

Discussion

Individual Data

- Consistent trend of positive correlation between aperture and peak EMG value
- Raw EMG variability across individuals

Group Data

- Non-linear relationship between aperture and EMG

Discussion

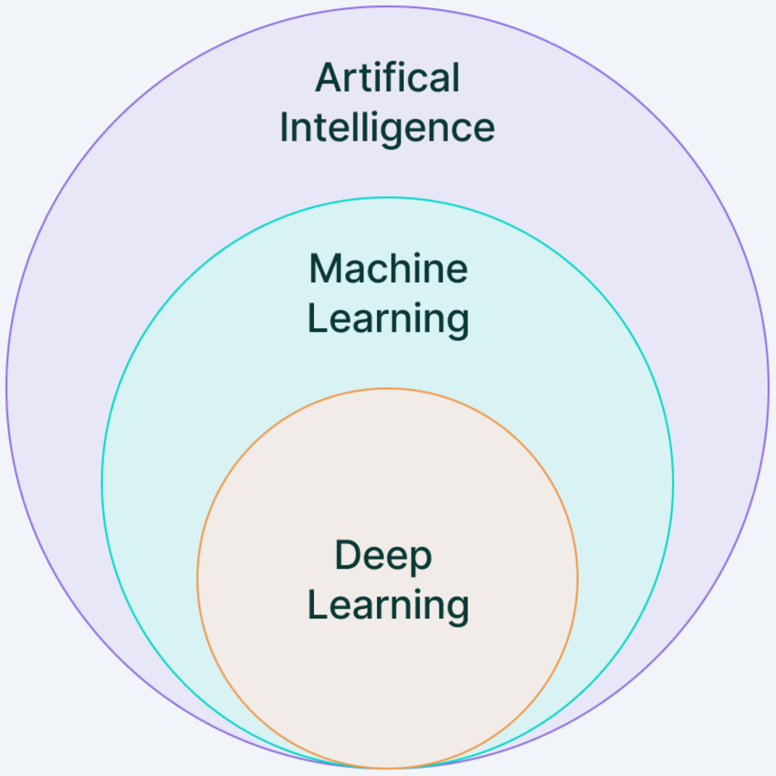
Future work

- Expand demographic to include non-male, post-stroke participants
- Fatigue and acquisition time caveat (Qing et al. [47], Wang et al. [48])
- **Further research should be directed towards developing models capable of extracting aperture from long-term, continuous EMG data.**

04

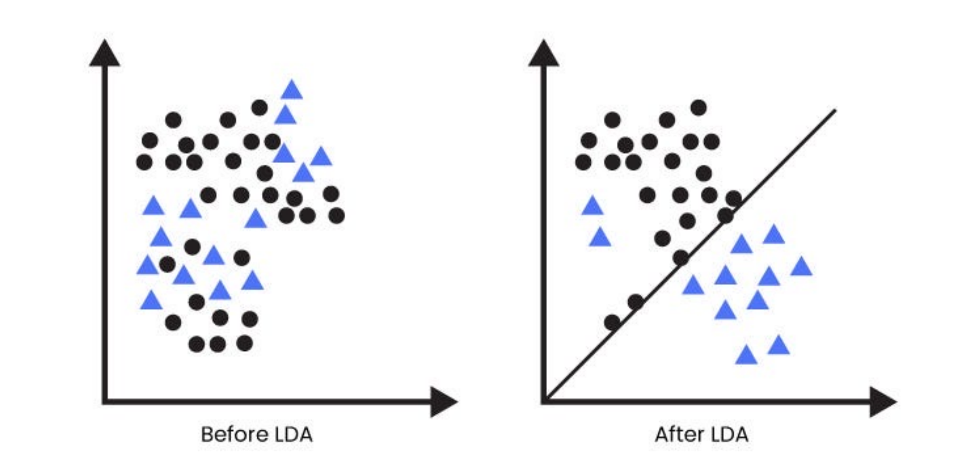
Classifying Human Activity Using Deep Learning: Background

Artificial Intelligence (AI)



Machine Learning

- Transformation of input data to classify between groups (classes)
- Train a model on existing data, test on unseen data



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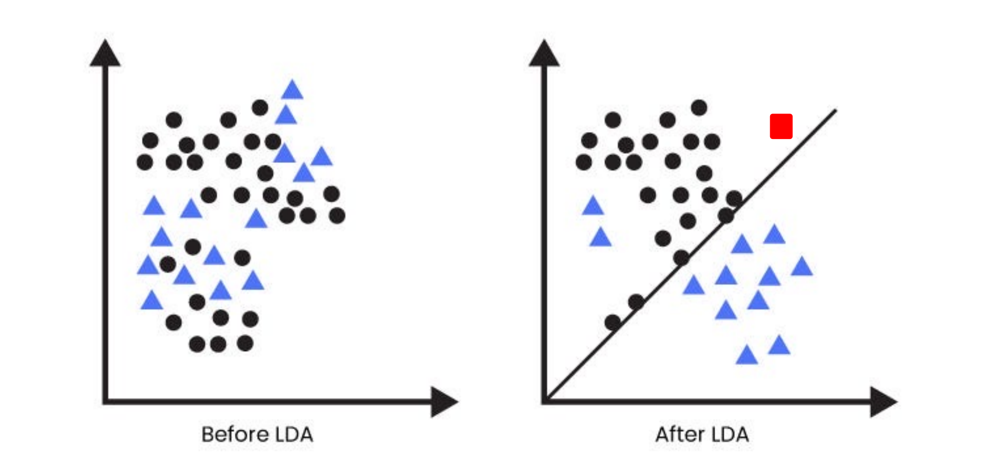

Machine Learning

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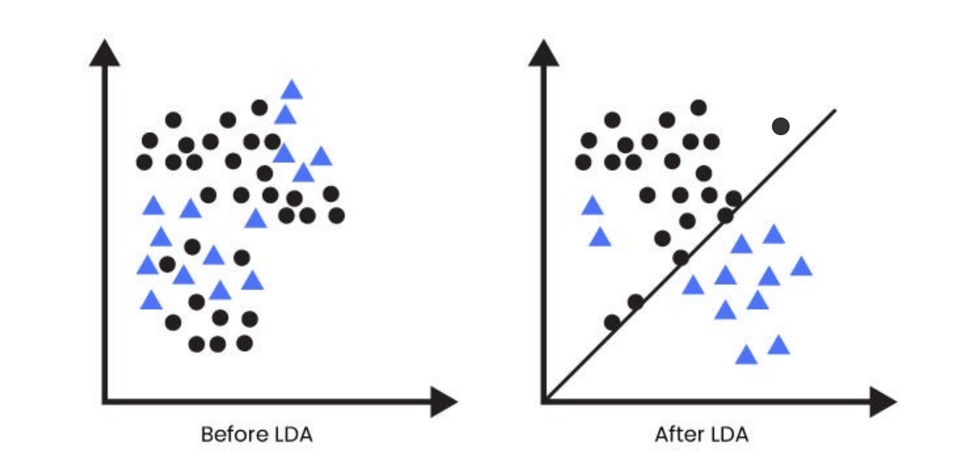
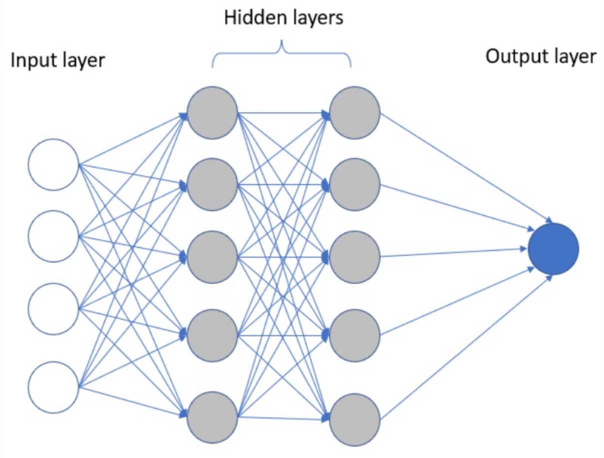
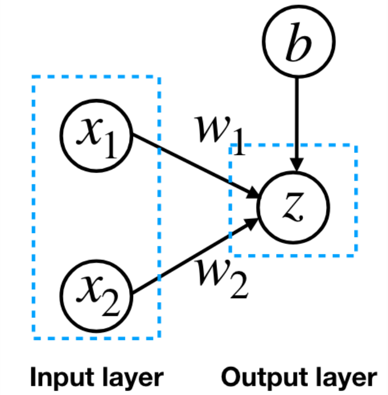


Deep Learning

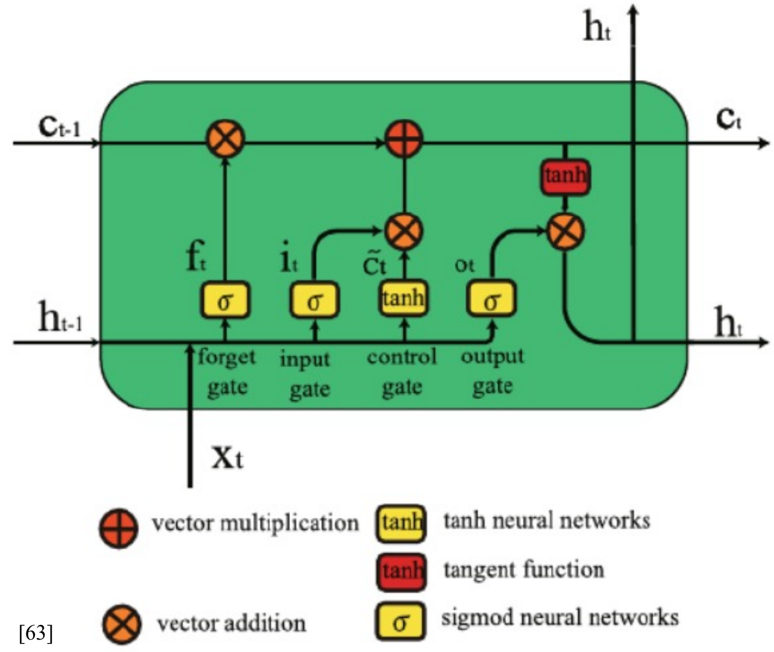
- Transformation of input data to classify between groups (classes)
- Train a model on existing data, test on unseen data
- Artificial neural network to transform input data





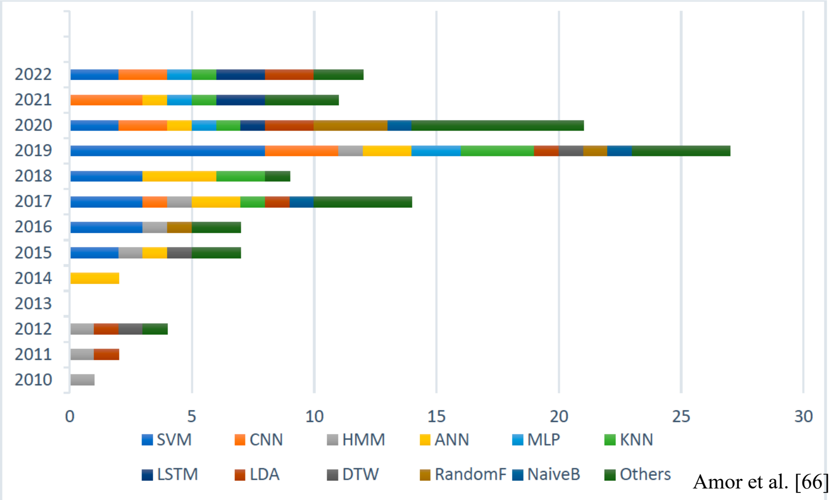
$$z = \sigma(Wx + b)$$

Recurrent Neural Network (RNN)



[63]

- Google Alexa, Apple's Siri

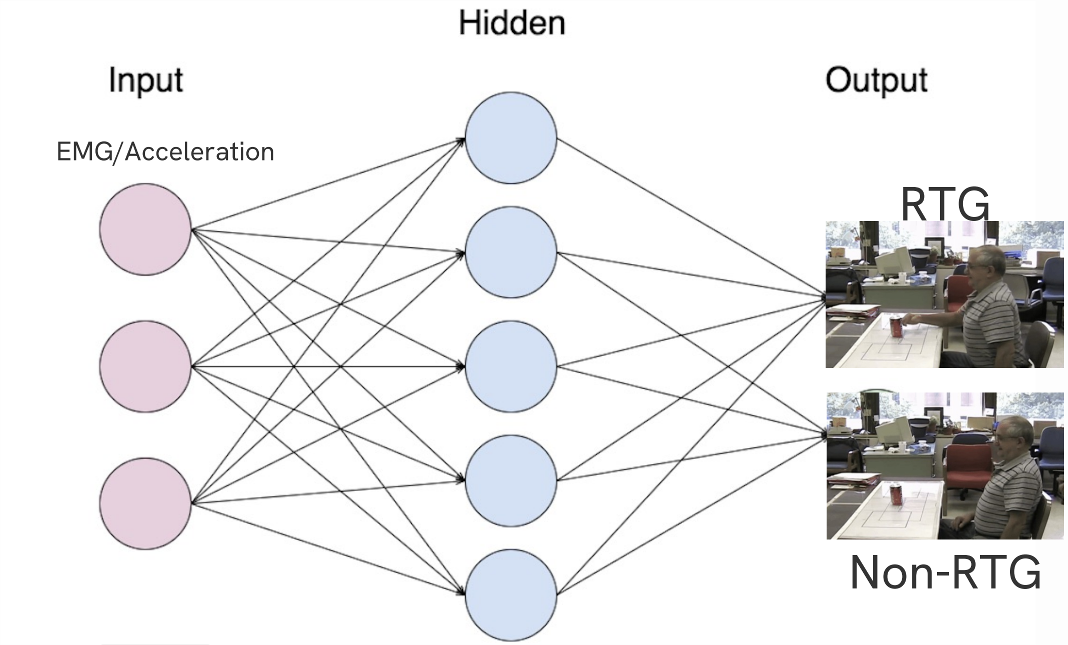


Amor et al. [66]

- Bidirectional Long-Short Term Memory (BiLSTM) widely used RNN

Contribution 2

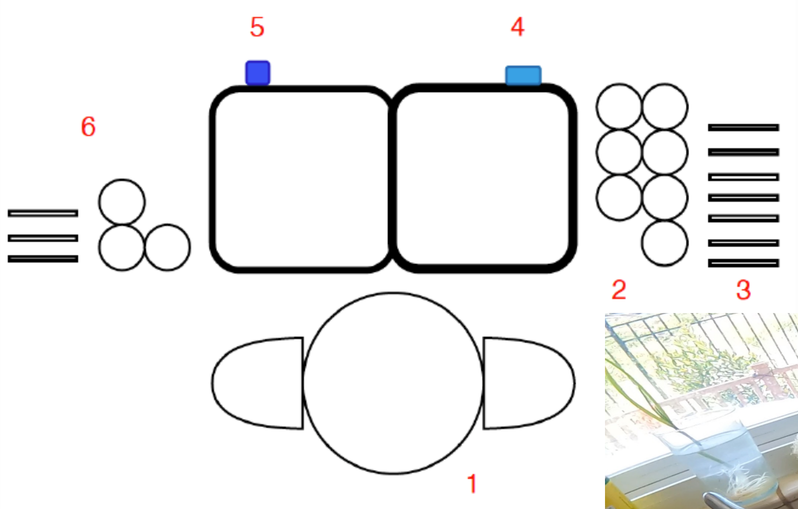
Can a neural network can be built to analyze EMG / acceleration data and determine if a person is performing a motor task?



05

Classifying Human Activity Using Deep Learning

Methods – Test Bench



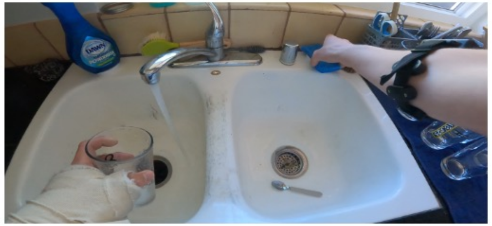
Item #	Description
1	Participant
2	Drink glasses before washing
3	Plates before washing
4	Sponge
5	Dish soap
6	Glass & plates after washing

Methods – Procedure

- 5:15 avg time per procedure
- ~80 RTG per procedure
- 8 procedures conducted
- ~640 RTG Instances

Methods – Data Labeling

```
timestamps = ["00:11:850", "00:14:060",
```



Video RTG occurs, timestamp recorded in MATLAB

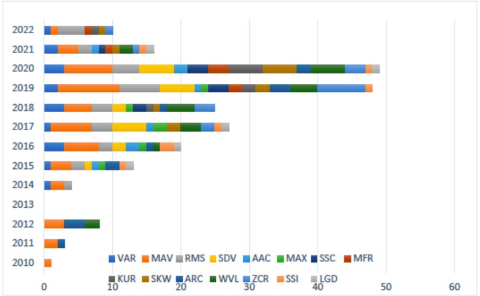
channel7	channel8	accelx	accely	accelz	class
-12791.1419415	3272.6257443	-0.62951499	0.791562915	0.091735605	1
-12868.963488	3499.17980085	-0.62951499	0.791562915	0.091735605	1
-12910.4489205	3640.2392664	-0.62951499	0.791562915	0.091735605	1
-12921.729417	3828.71170035	-0.62951499	0.791562915	0.091735605	1
-12931.231005	3953.9878353	-0.62951499	0.791562915	0.091735605	1
-12927.3525945	4023.31696695	-0.62951499	0.791562915	0.091735605	1
-12930.36975	4062.37398615	-0.62951499	0.791562915	0.091735605	0
-12930.36975	4062.37398615	-0.62951499	0.791562915	0.091735605	0
-12879.8452575	4184.86218435	-0.638975415	0.797422275	0.104064675	0

375 samples
With 1 label

Data export to Python, appending class labels at timestamps

Methods – Feature Extraction

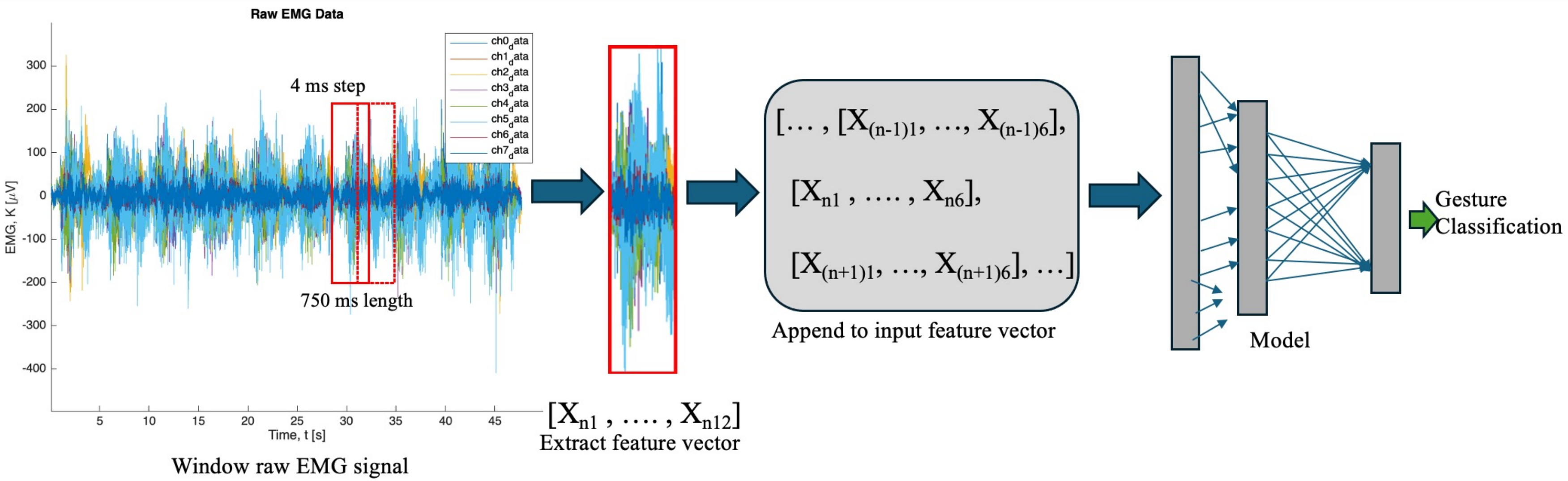
Feature	Formula	Description
Mean Absolute Value (MAV)	$MAV = \frac{1}{N}\sum_{i=1}^{N} \lvert x(i) \rvert$	Single metric by which overall amplitude can be measured
Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$	Magnitude or power of a signal
Waveform Length (WL)	$WL = \sum_{i=1}^{N-1} \lvert x(i+1) - x(i) \rvert$	Represents the total variation or complexity of a signal
Standard Deviation (STD)	$STD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2}$	Indication of a signal noise and variability
Zero Crossing (ZC)	$ZC = \sum_{i=1}^{N-1}((x_i \cdot x_{i+1}) < 0)$	Count of times a signal changes its sign, indicating frequency content
Sign Slope Change (SSC)	$SSC = \sum_{i=2}^{N}((x_{i-1} - x_{i-2}) \cdot (x_i - x_{i-1}) < 0$	Count of times a signal changes its slope direction, indicating signal complexity



Amor et al. [66]

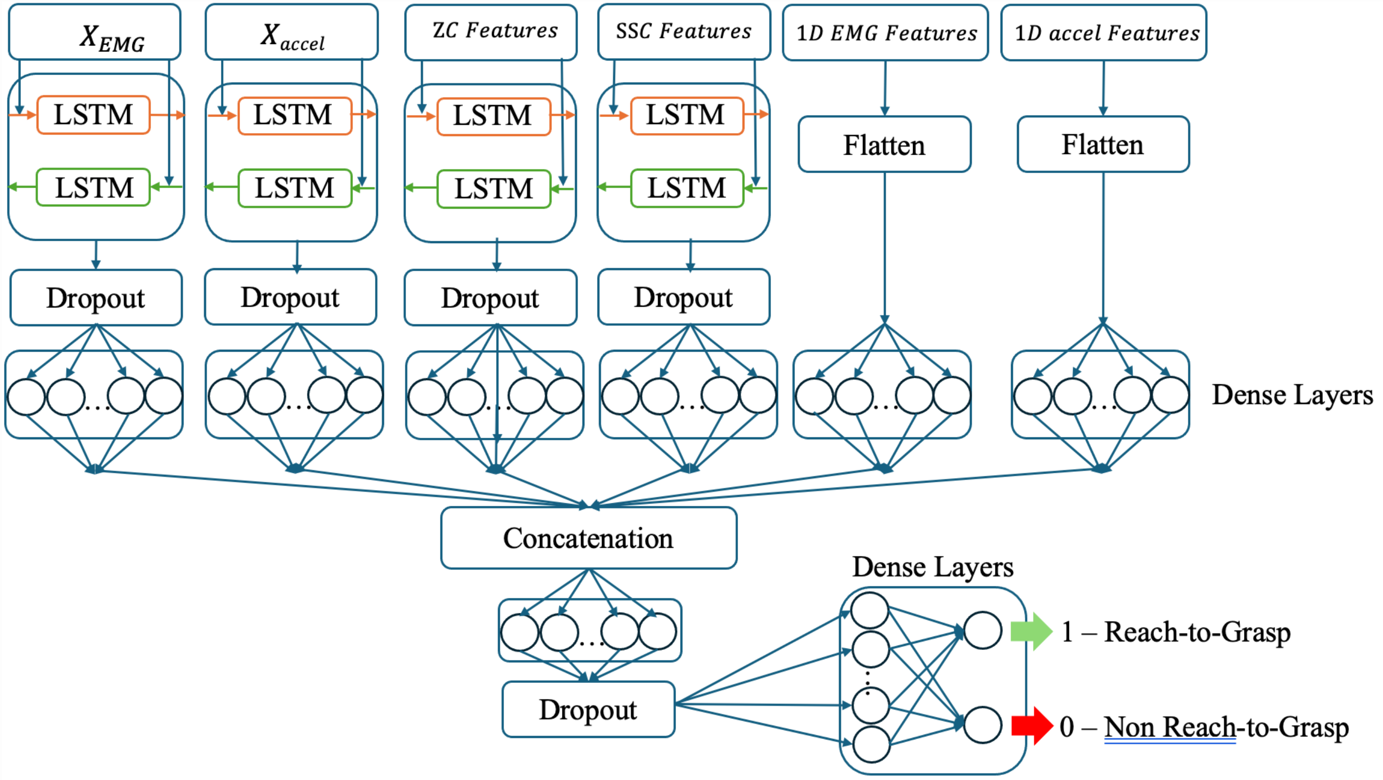
- In addition to raw EMG/acceleration data, hand selected relevant features
- Selected features most prevalent in EMG and audio processing

Methods – Feature Extraction



- Sliding window of 750 ms (375 samples) length, 4 ms (20 samples) overlap
- Assign 0 or 1 value to each window using thresholding technique

Methods – Model Architecture



Methods – Model Architecture

Branch	Layer Parameters	Value	Model Parameter	Value
$X_{EMG}X_{acc}$	Bi-LSTM Cells	100	Optimizer	Adam
	Dense Nodes	100	k-fold cross-val	n-folds = 5
	Dropout	0.50	Learning Rate	0.001
ZC, SSC	Bi-LSTM Cells	100	Class Weights	Balanced
	Dense Nodes	100	Activation Functions	Relu
	Dropout	0.30		Softmax
1-D EMG, Accel Features	Dense Nodes	100	Epochs	60
Concatenated	Dense 1 Nodes	100	Batch Size	256
	Dense 2 Nodes	12		
	Dense 3 Nodes	2		
	Dropout	0.3		

Results – Evaluation Metrics

- Accuracy / Loss are two standard metrics for model performance
- In class imbalanced problems, must inspect other metrics

Metric	**Formula**	**Description**
Accuracy	$A = \frac{1}{N}\sum_{i=1}^{N} f(\hat{y}_i = y_i)$	Proportion of correctly classified samples
Loss	$L = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} \cdot \log(p_{i,c})$	Quantifies error made by the model
Precision	$P = \frac{TP}{TP+FP}$	Proportion of true positives to all predicted positives
Recall	$R = \frac{TP}{TP+FN}$	Proportion of true positive among all actual positives
F1-Score	$F1 = 2 \cdot \frac{P \cdot R}{P+R}$	Single metric to assess performance by

Results – Evaluation Methods

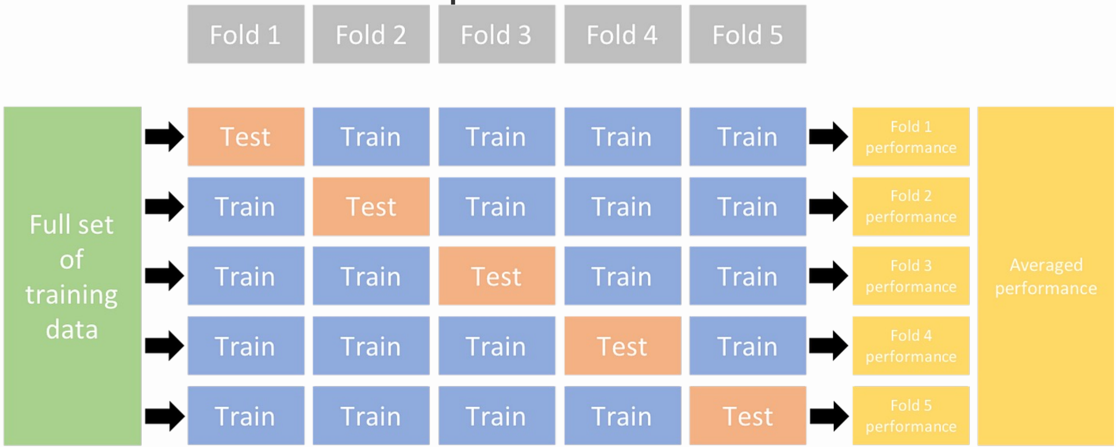
2 Methods for evaluating model performance

1. **K-fold Cross validation**

   -Decreases model bias, better assessment of generalizability

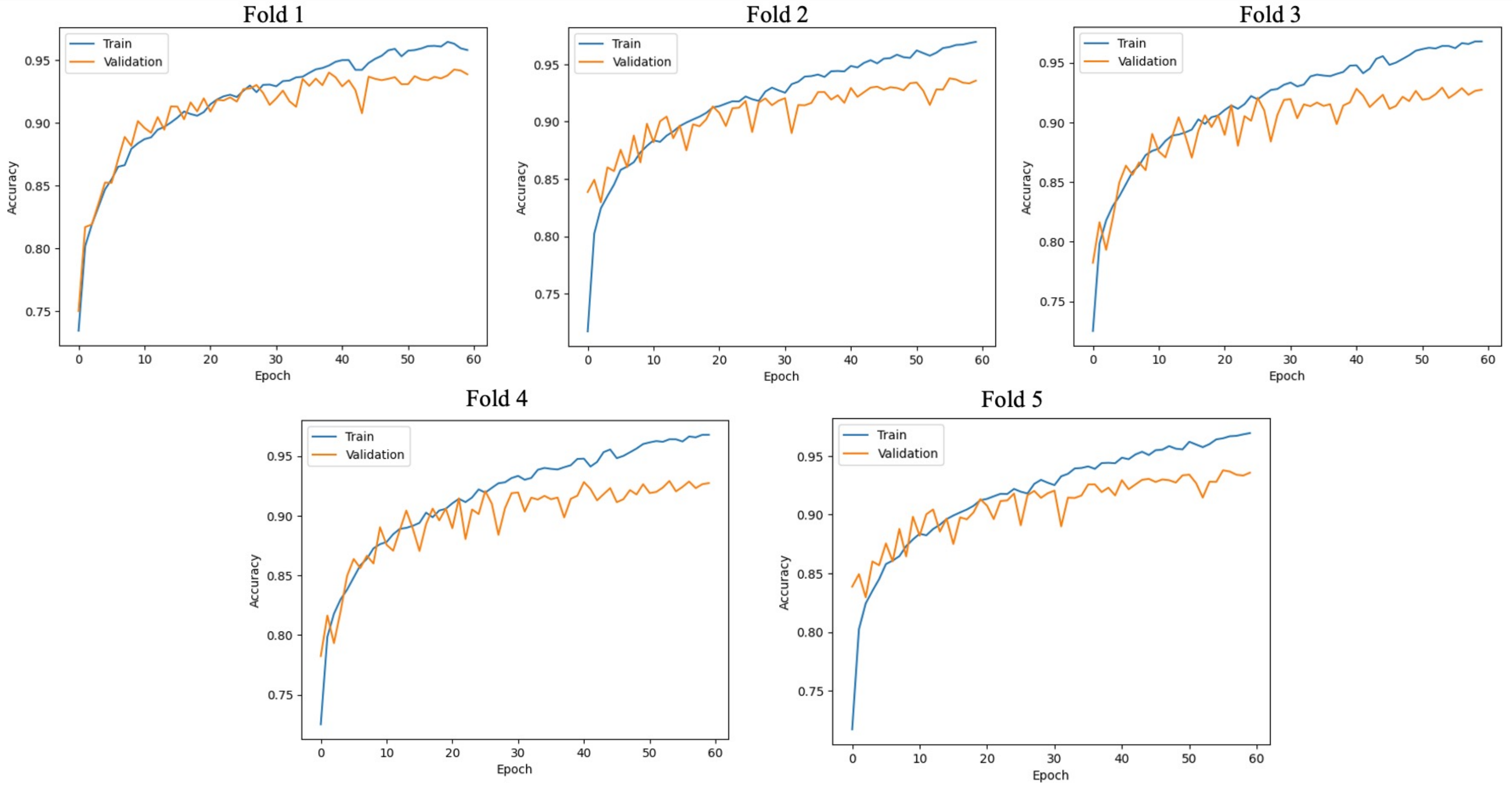
2. **Training on limited data**

   -Assess model reliance upon data for end use-case

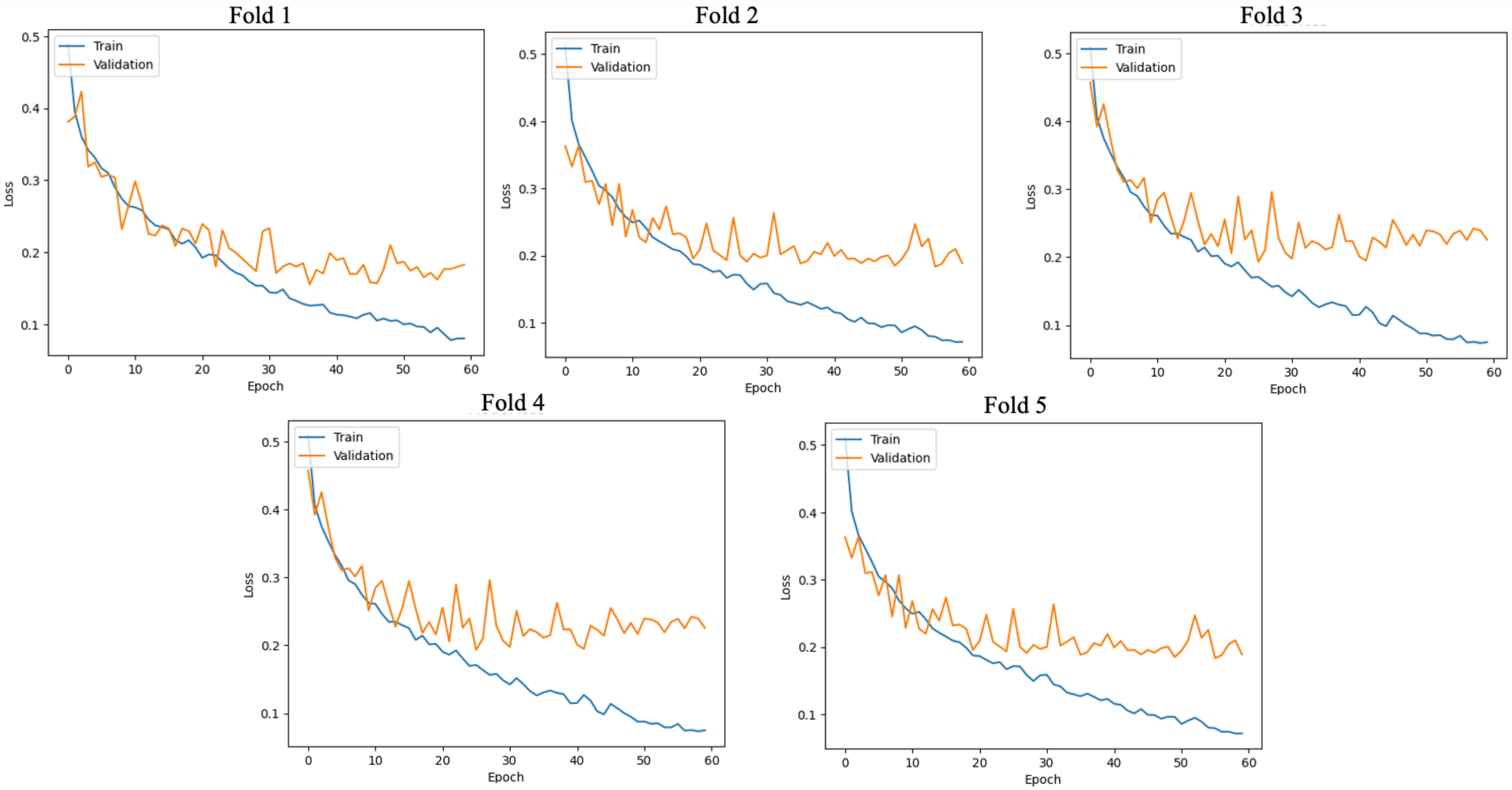


https://docs.ultralytics.com/guides/kfold-cross-validation/

Results – K-fold Cross Validation



Results – K-fold Cross Validation

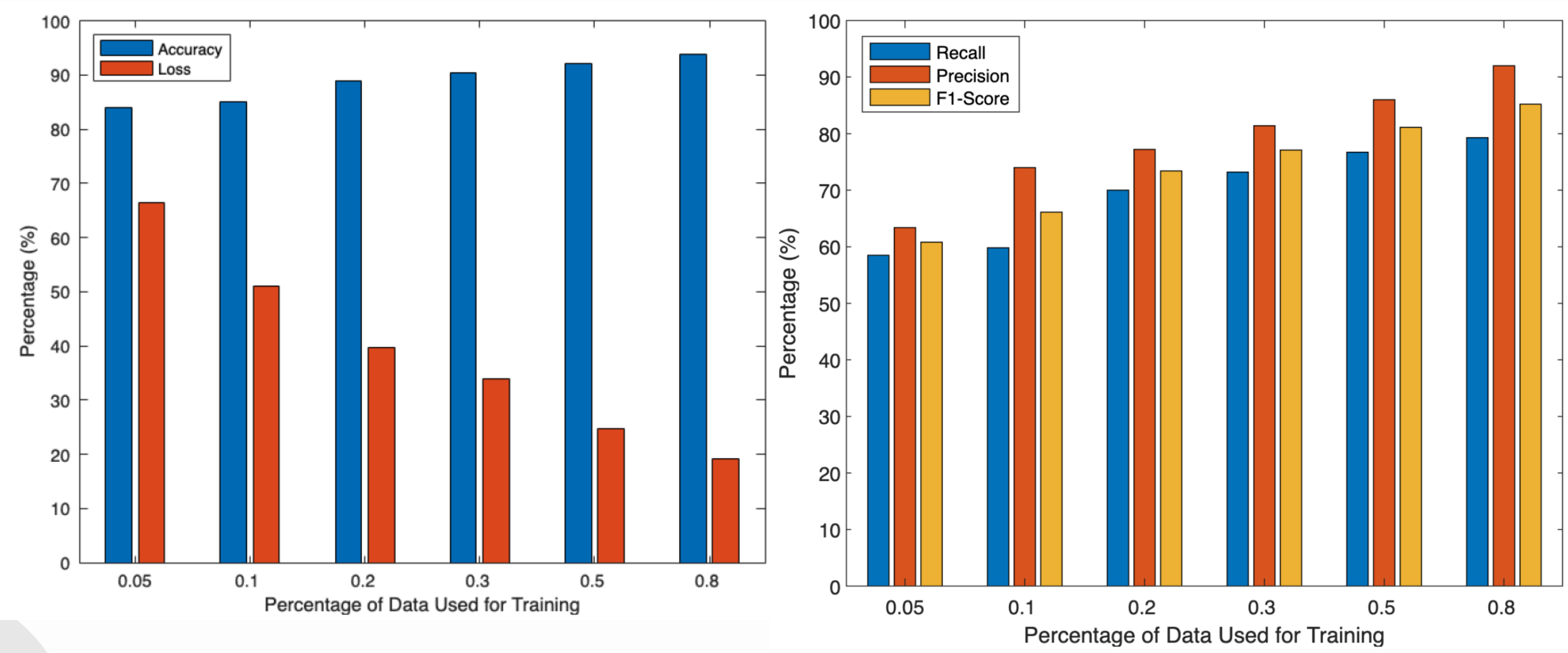


Results – K-fold Cross Validation

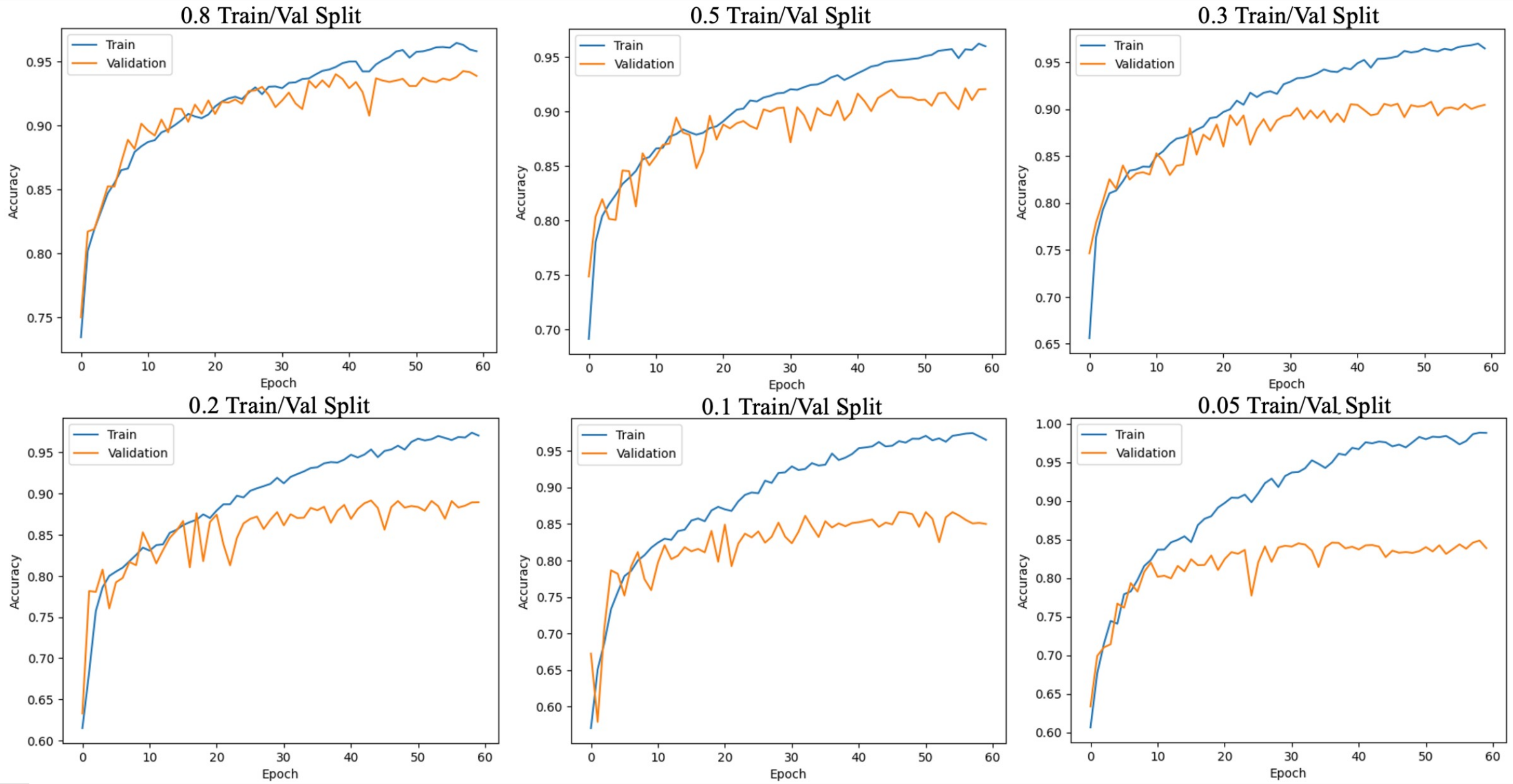
Averaged Model Performance

Accuracy	Loss	Recall	Precision	F1 Score
0.927	0.226	0.900	0.770	0.830

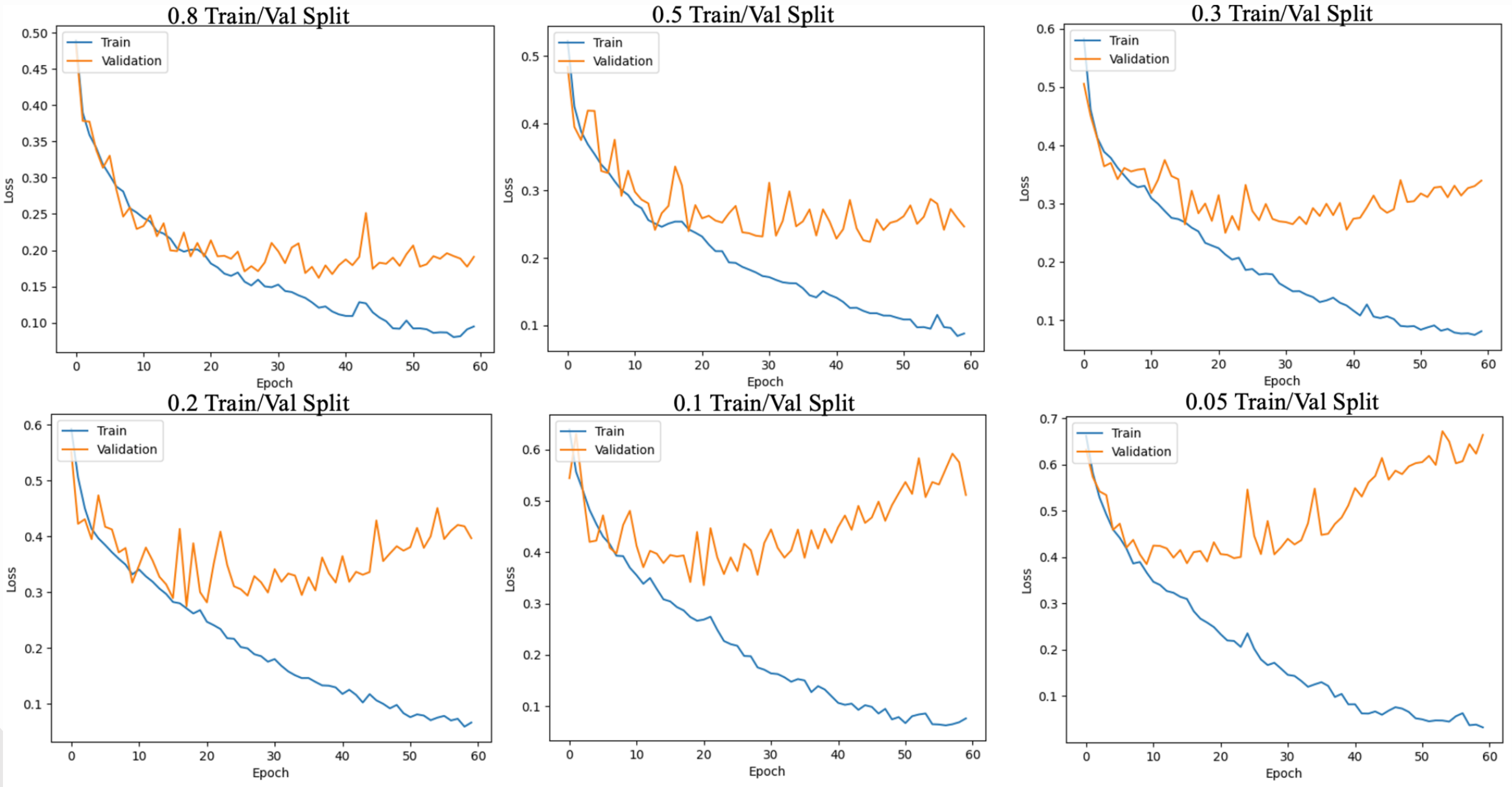
Results – Training using limited data



Results – Training using limited data



Results – Training using limited data



Results – Training using limited data

Data Split	Accuracy	Loss	Recall	Precision	F1 Score
0.8	0.939	0.191	0.920	0.793	0.852
0.5	0.921	0.247	0.860	0.767	0.811
0.3	0.905	0.339	0.814	0.732	0.771
0.2	0.890	0.397	0.772	0.700	0.734
0.1	0.850	0.511	0.740	0.598	0.661
0.05	0.839	0.664	0.634	0.585	0.608

Discussion

- F1-score and loss comparable to existing literature [64, 79, 80]
- Model over-predicted RTG instances
- Recommended to include over 50% of data for training

Future Work

- Implement a CNN-LSTM Hybrid model [32], regularization
- Classify between more classes
- Include variety of tasks
- Expand demographic to post-stroke individuals

06

Discussion

Summary

Contribution 1

- Characterized relationship between EMG and grip aperture
- Developed novel grip aperture acquisition technique

Contribution 2

- Designed procedure simulating a functional in-home task
- Engineered data processing pipeline for EMG and video analysis
- Built model architecture capable of extracting ADL execution from long-term, continuous data in the home setting

Summary

Total Contribution

- Contribution 1 creates knowledge base for aperture and EMG relationship
- Using contribution 1, utilize model to extract aperture from continuous EMG data in home setting using deep-learning

Contribution 1 in press for IEEE EMBC Conference

Contribution 2 journal paper, targeting IEEE JBHI, TNSRE

Special thanks to Dr. Espinoza-Wade, Dr. Klisch, and Dr. Ventura for your guidance and support. Thank you to my family for your inspiration and support

06

Q&A