

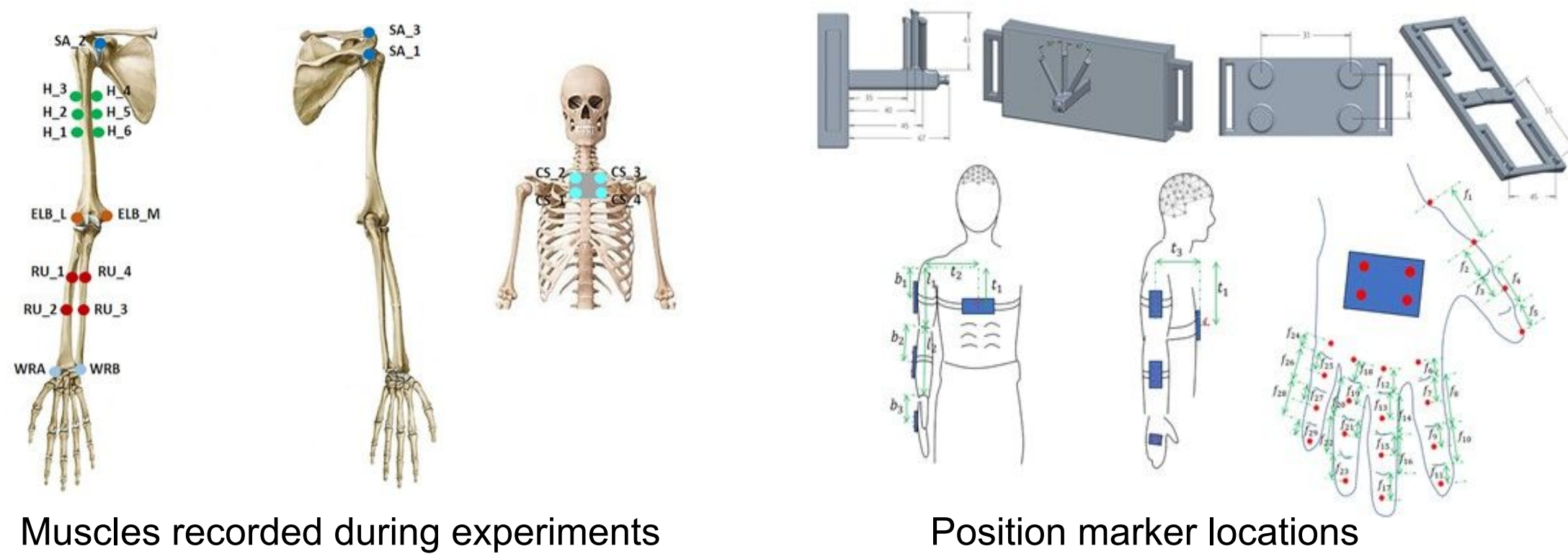
Developing a Tool for Sensor Based Clinical Evaluation (SenBaCE)

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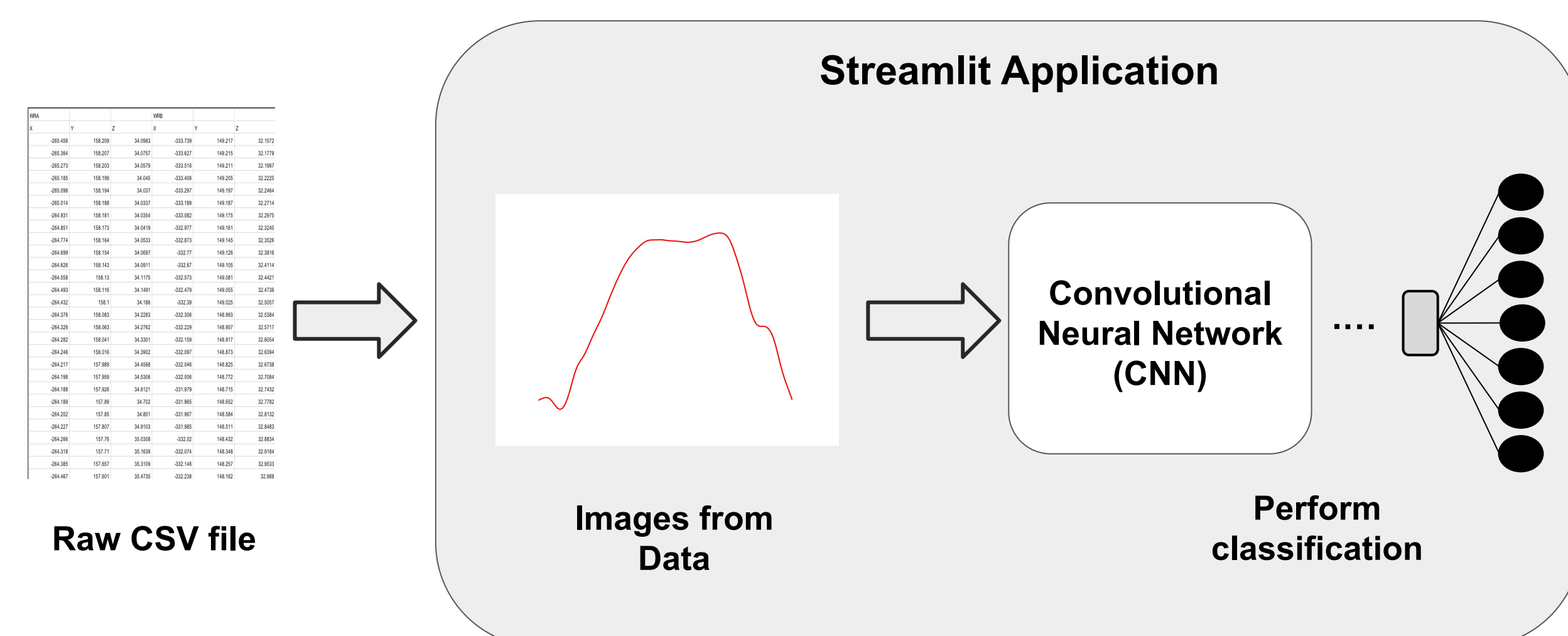
Introduction and Background

- Standard clinical practice involves visual assessments of motor tasks to clinically rate motor impairments.
- Sensor data (i.e. IMU, optical markers, electromyography (EMG)) help quantify motor activity, but there is a gap in making them clinically relevant.
- Here, we demonstrate the use of images generated from positional sensor data to train a convolutional neural network (CNN) to assign clinical scores and deploy it on Streamlit.



Data and Design

- Dataset
 - U-Limb: large, multimodal, multi-center dataset on human upper-limb movements.
 - Kinematic data - with position data of thorax, upper-and forearm markers.
- User Interface (Streamlit Web App)
 - Primary users - Clinician and Researcher/ML
 - Enable prediction of scores (Clinician)
 - Enable training (Researcher/ML)
 - Allow for data import and export
- Processing and ML Pipeline (PyTorch, Pandas, Pillow)



Dashboard and Deploying ML model

1. Load data page

Load Data

Patient Name: Jack Gill

You entered: Jack Gill

Choose a file: 01_1_3.csv 23.9KB

Predicting with a Pretrained Model

Predict Scores

Default training model will be used to predict score.

Predicted score for 01_1_3-WRA-Y: [19]

Predicted score for 01_1_3-WRA-X: [18]

Predicted score for 01_1_3-WRA-Y: [14]

Plots from Raw Data

Plot for 01_1_3-WRA-X

Plot for 01_1_3-WRA-Y

Plot for 01_1_3-WRA-Y.1

Plot for 01_1_3-WRA-Y

2. Training and prediction page

Upload files

Choose an image file: 01_1_3-WRA-Y.png 97.8KB, 01_1_3-WRA-Y.1.png 93.5KB, 01_1_3-WRA-X.png 110.0KB

Choose a scores file: subjects_FMA_scores.csv 103.0B

Hyperparameters

Batch Size: 1

Epochs: 20

Learning Rate: 1e-05

Export Trained Model

Training Results

Training Accuracy (%)

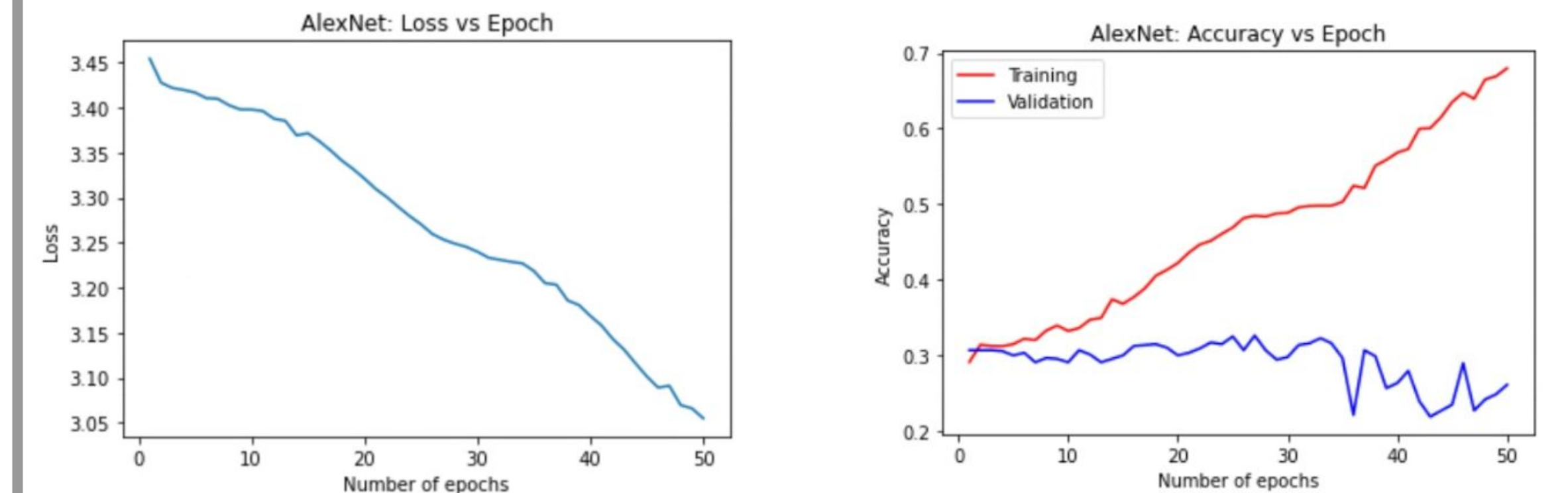
Training Loss vs Epoch

Challenges/Limitations

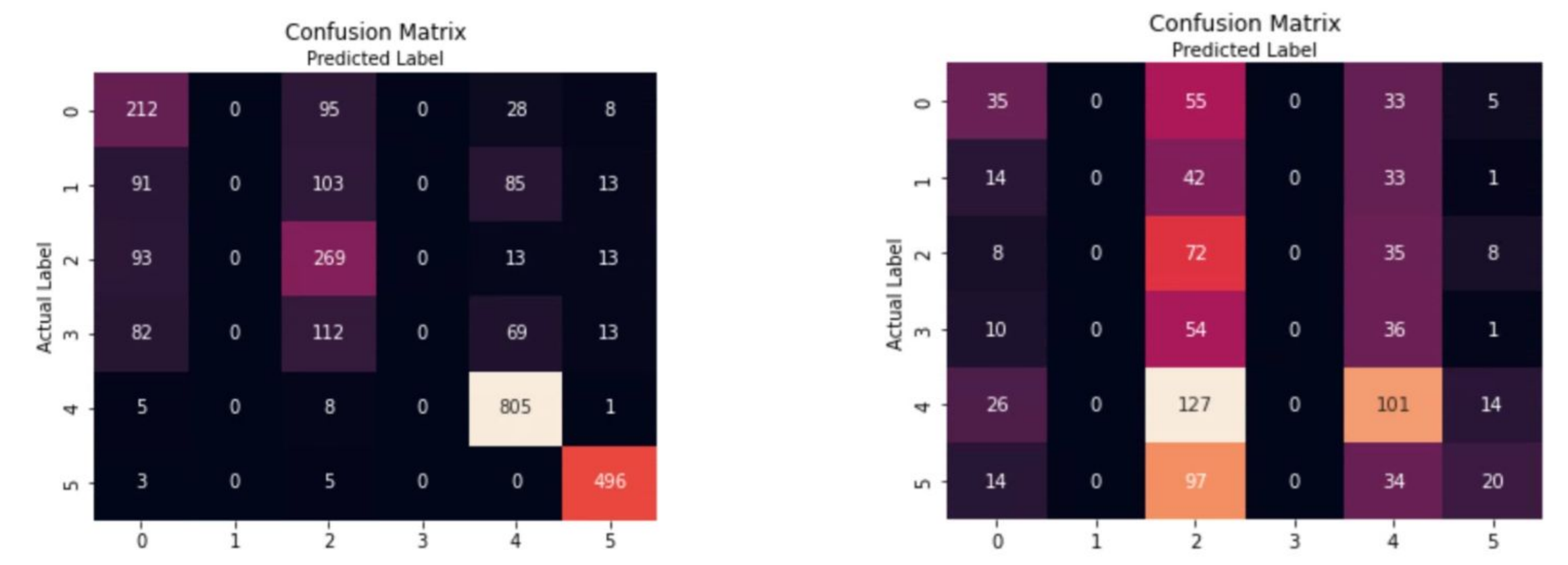
- Lower Accuracy: despite image size (227x227), very simple features (just red line) to train with.
- Many image files to load and train the data competed with limited resources.
- Uneven distribution of data, even within more severely impaired patients.

Machine Learning Results

AlexNet:

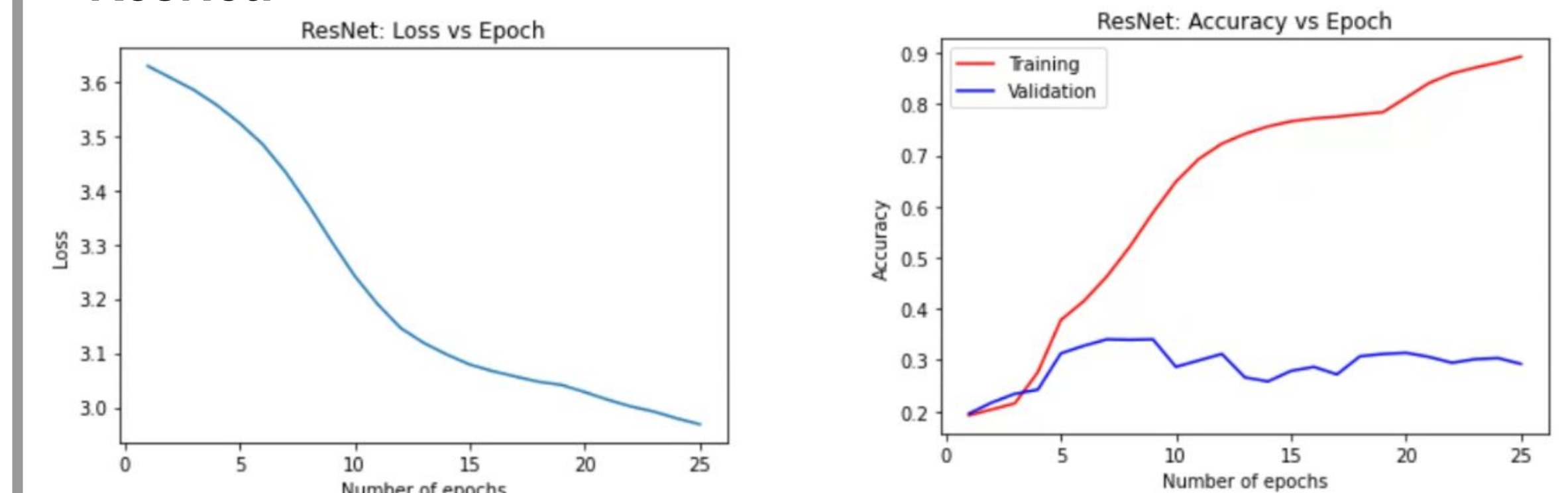


Performance of an AlexNet model trained for 50 epochs with a learning rate = $5e-6$ and L2 regularization penalty = $1e-4$, yielding a test accuracy of 33.98%.

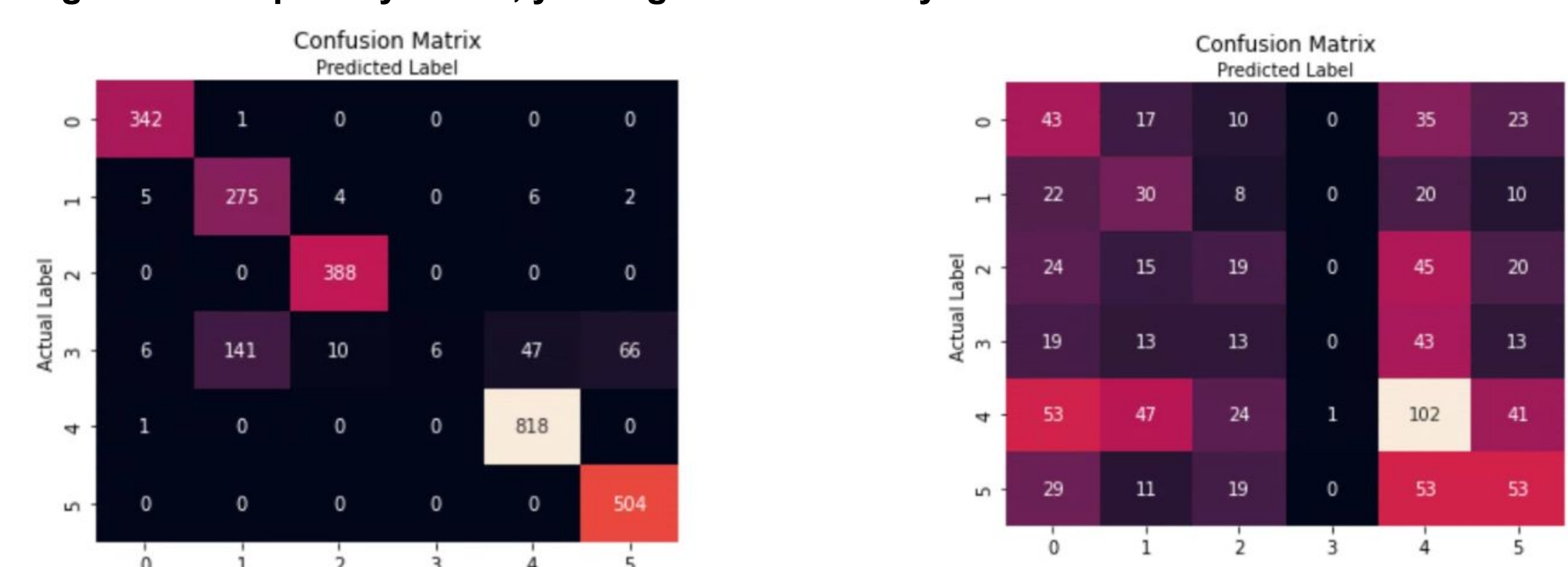


Confusion matrices for training (left) and validation (right) datasets with AlexNet.

ResNet:



Performance of an ResNet model trained for 25 epochs with a learning rate = $5e-6$ and L2 regularization penalty = $1e-4$, yielding a test accuracy of 33.52%.



Confusion matrices for training (left) and validation (right) datasets with ResNet.

Future Work

- Additional data for more equally distributed dataset.
- Expand data processing pipeline (i.e. EMG).
- Explore simpler models to decrease complexity and improve accuracy.
- Incorporate additional features through Streamlit interface (e.g., UI modification).