ECE-4099: Capstone Project

FINAL PRESENTATION
4th May 2022

Project details:

TITLE:

EMG Analysis for Rehabilitation Assessment

GUIDE:

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Motivation:

1. There are many situations where a person's physical and motor abilities might become impaired (neurological disorders, accidents, etc.,).
2. As treatment, remedy is prescribed to the patients in the form of exercises. However, it is difficult for the physiotherapists to continuously monitor whether or not the patient is performing those exercises correctly.
3. Electromyography (EMG) signals are bioelectrical signals that tell us about the behaviour of the muscles in the body.
4. By acquiring and processing those signals, it is possible to assess whether or not the exercises are being performed correctly and consequently, establish whether or not the rehabilitation is effective.

Objective:

To design a Biofeedback System to assess the effectiveness of exercises by processing the signals to classify correctly and incorrectly done exercises, and displaying the results on a GUI.

Literature Survey (1/3):

S.NO	SOURCE	METHODOLOGY	IMPLICATIONS
1	McManus, Lara, et al. “Analysis and Biophysics of Surface EMG for Physiotherapists and Kinesiologists: Toward a Common Language With Rehabilitation Engineers.” Frontiers in Neurology, vol. 11, no. 10.3389/fneur.2020.576729, 2020. Frontiers, https://www.frontiersin.org/article/10.3389/fneur.2020.576729 **Publisher: Frontiers Media**	• Methods to find abnormal patterns in EMG signals. • Acquisition of EMG amplitude, acceleration. • RMS and ARV calculation to determine muscle force. • PSD, mean and median frequency to ascertain muscle fatigue.	• Possible to find out degree of muscle activation in time-domain (amplitude) analyses. • Gait from gyroscope data. • Muscle fatigue and time-to-task failure can be determined from frequency-domain. • Noise sources.
2	Palumbo A, Vizza P, Calabrese B, Ielpo N. Biopotential Signal Monitoring Systems in Rehabilitation: A Review. Sensors (Basel). 2021 Oct 28;21(21):7172. doi: 10.3390/s21217172. PMID: 34770477; PMCID: PMC8587479. **Publisher: NCBI**	• Instrumentation of the hardware components including amplification, • ADC, wireless transmission. • Databases chosen: PubMed, MDPI, Springer, ACM Digital Library and Science Direct. • Discusses which of the proposed methods of acquiring and processing is best: AFEs, ADCs, etc	• Discusses what parameters should be used to assess a system’s efficiency: accuracy, CMRR, SNR, etc., • Provides a possible architecture for low-cost, low-energy, light-weight biosensing systems.

Literature Survey (2/3):

S.NO	SOURCE	METHODOLOGY	IMPLICATIONS
3	Zhao S, Liu J, Gong Z, Lei Y, OuYang X, Chan CC, Ruan S. Wearable Physiological Monitoring System Based on Electrocardiography and Electromyography for Upper Limb Rehabilitation Training. Sensors (Basel). 2020 Aug 28;20(17):4861. doi: 10.3390/s20174861. PMID: 32872111; PMCID: PMC7506771. **Publisher: NCBI**	● Discusses the RMS evaluation of EMG signals. ● Demonstrates how to evaluate muscle fatigue and muscle intensity. ● Methods to integrate sensors and preprocessing in BLE Module. ● Discusses instrumentation for adaptive feedback based on real-time results.	● Greater frequency of RMS signal implies stronger activity, lesser frequency -> weak activity. ● Evaluating the muscle fatigue using PSD. ● Techniques on evaluating extracted features using SVM.
4	Beretta-Piccoli, Matteo, et al. "Reliability of surface electromyography in estimating muscle fiber conduction velocity: A systematic review." Journal of Electromyography and Kinesiology, vol. 48, 2019, pp. 53-68. Science Direct, https://www.sciencedirect.com/science/article/pii/S1050641118303110. **Publisher: Elsevier**	● Establishes whether or not MFCV is a reliable parameter extracted from sEMGs. ● Databases examined: PubMed, Web of Science. ● 17 studies met the eligibility criteria. ● Test-retest, intrasession, intersession reliability were evaluated.	● 8 of the studies reported that it is useful to assess the initial and mean MFCV value. ● Most efficient when EMG electrodes are used to evaluate muscle fibres that run parallel to the skin.

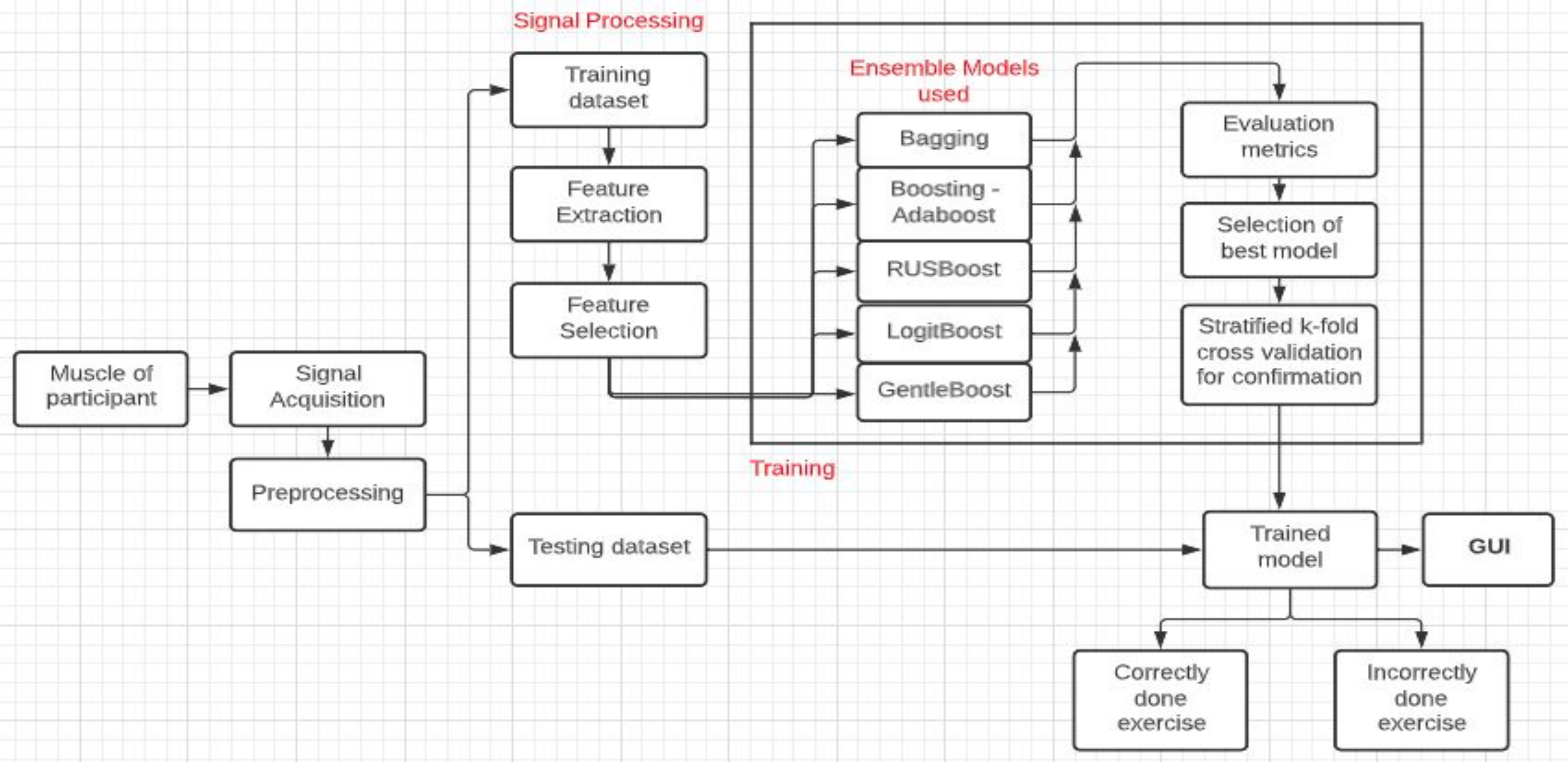
Literature Survey (3/3):

S.NO	SOURCE	METHODOLOGY	IMPLICATIONS
5	Lee SSM, Lam T, Pauhl K, Wakeling JM. Quantifying muscle coactivation in individuals with incomplete spinal cord injury using wavelets. Clin Biomech (Bristol, Avon). 2020 Mar;73:101-107. doi: 10.1016/j.clinbiomech.2020.01.001. Epub 2020 Jan 7. PMID: 31958701. **Publisher: NCBI**	● Frequency components are extracted using frequency decomposition. ● Wavelet convolution was used for feature extraction. ● Normalised values for normal and injured muscles were significantly different thus enabling easy classification.	● Frequency-dependant differences in muscle activity. ● Feature extracted: coactivation of different motor units. ● Such differences imply changes in muscle recruitment patterns.
6	Taborri J, Keogh J, Kos A, Santuz A, Umek A, Urbanczyk C, van der Kruk E, Rossi S. Sport Biomechanics Applications Using Inertial, Force, and EMG Sensors: A Literature Overview. Appl Bionics Biomech. 2020 Jun 23;2020:2041549. doi: 10.1155/2020/2041549. PMID: 32676126; PMCID: PMC7330631. **Publisher: NCBI**	● Feature extraction of sEMG signals: amplitude, frequency, power, energy, etc., ● Classification of features using k-means, SVM. ● Nonlinear analyses: Lyapunov exponents. ● PCA to extract muscle synergies.	● Can be used to review effects of different exercises. ● Statistical validation of these results could be applied in other rehab domains.

Hardware and Software details:

1. Disposable surface EMG electrodes - 9 inch leads as sensors to detect the raw EMG signals.
2. ADS1292R Embedded board (24-bit ADC, 2 channels) for data acquisition.
3. LogAndStream v.0.6.0 for wireless bluetooth transmission
4. MATLAB R2020a version for processing

Overall flow of the project:

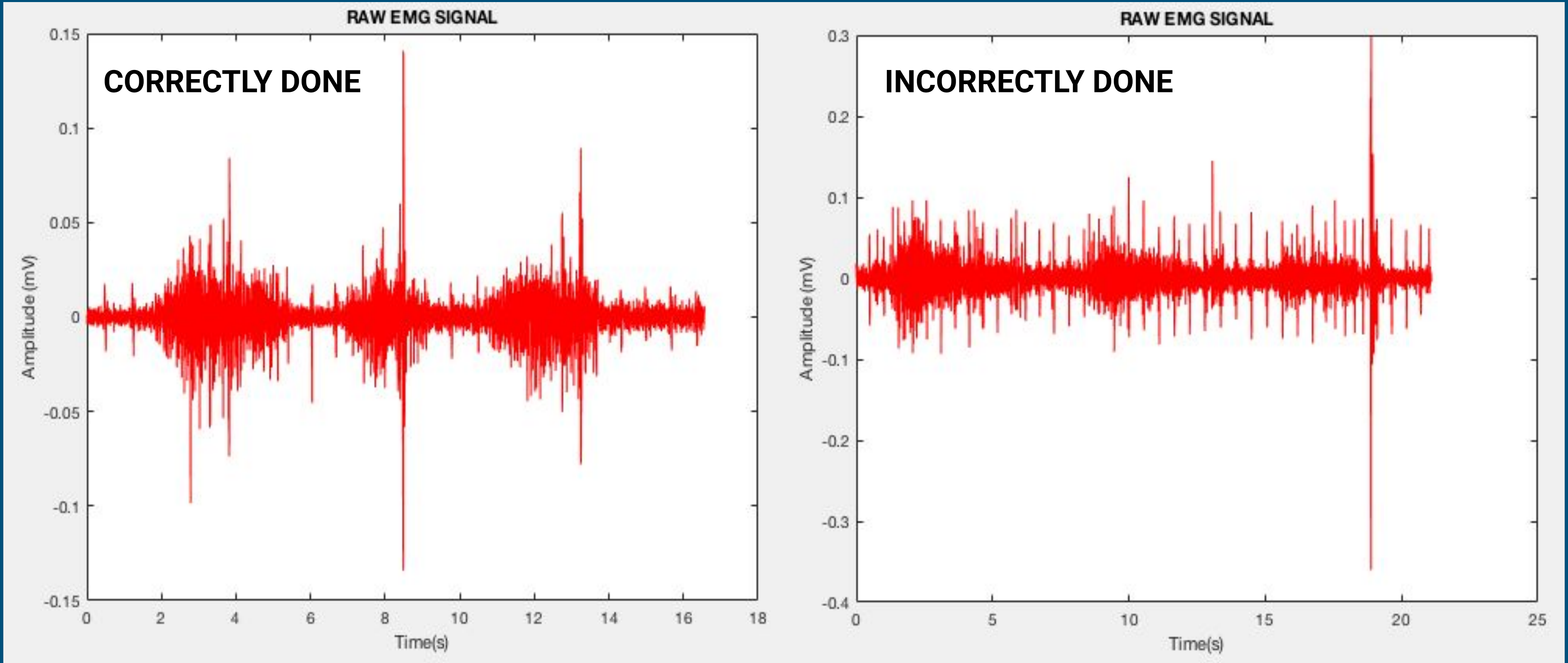


Methodology:

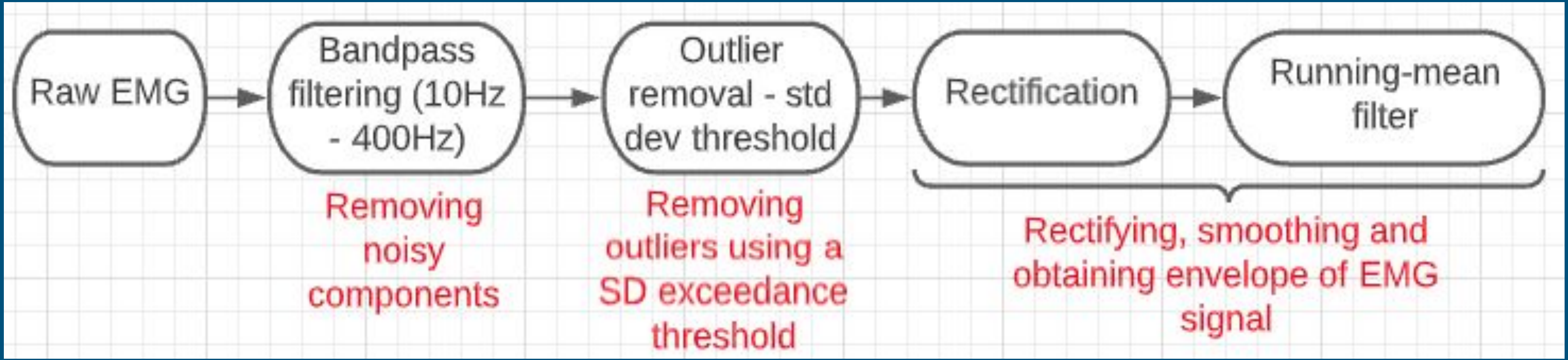
1. EMG signals are first acquired for 7 different exercises from patients. The signals are taken for both correctly and incorrectly done exercises.
2. Once acquired, the signals are taken for preprocessing.
3. The filtered, denoised and smoothed signals are taken for feature extraction.
4. 10 different features were extracted from the signals across different domains (time, frequency, time-frequency and nonlinear).
5. Feature selection is done to select the best possible features for classification.
6. The selected features are used as input to the classifier.
7. The classifier would then classify the EMG signals to tell us whether or not the exercises are being performed correctly.
8. The whole setup, starting from preprocessing to classification, is incorporated into a GUI for the users to access.

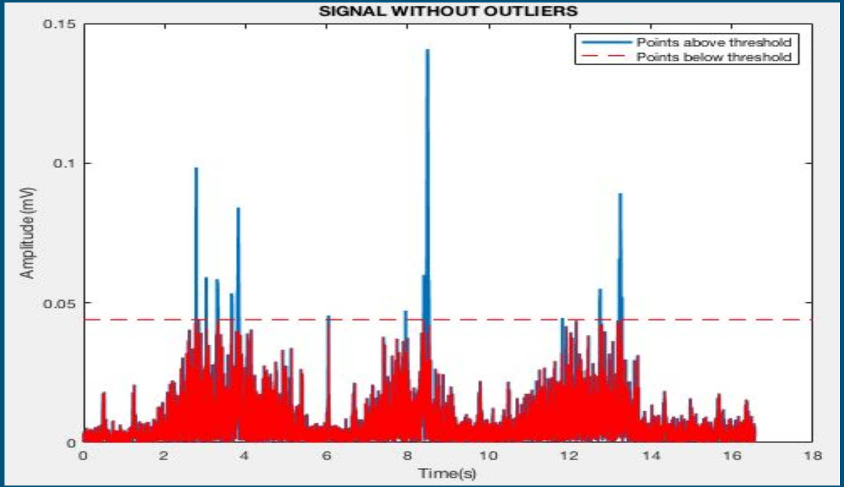
SECTION-1: Preprocessing

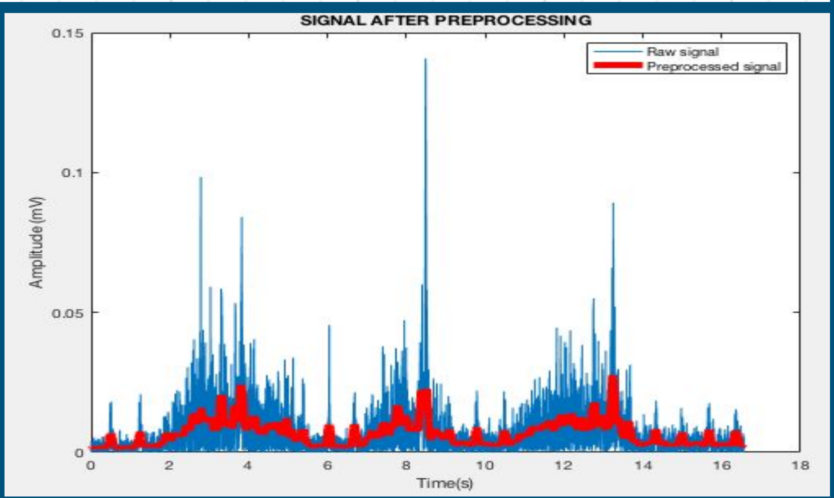
Sample EMG signals of correct and incorrect:



Preprocessing:







SECTION-2:
Feature Extraction

Feature Extraction:

FEATURE	DESCRIPTION	INFERENCE
Power	Maximum power of signal is related to spectrum analysis and is calculated using STFT.	It tells us about the maximum power contained in a correct/incorrect EMG signal and helps in analysis.
DFA - Hurst exponent	A nonlinear feature that tells us about the degree of self-affinity in a signal.	EMG signals are nonstationary signals, their characteristics vary with time. Tells us about the predictability of the later part of a signal in comparison to its initial parts.
Energy	It is the area under the squared magnitude of signal.	Tells us about how much energy is contained within the signal. Goal was to see if correctly done exercises had more/less energy.
D_median	Median of detailed coefficients of the 10th level, 1st order Daubechies wavelet decomposition	WT reduces crosstalk between different muscles. In the 10th level of WT and decomposition, it tells us if the median of the EMG signal shows characteristics that can differentiate between correct and incorrect.
D_rms	RMS of detailed coefficients of the 10th level, 1st order Daubechies wavelet decomposition	WT reduces crosstalk between different muscles. In the 10th level of WT and decomposition, it tells us if the RMS of the EMG signal shows characteristics that can differentiate between correct and incorrect.

Feature Extraction: (contd.)

FEATURE	DESCRIPTION	INFERENCE
Approx. Entropy	Approximate entropy is a regularity statistic that quantifies the unpredictability of fluctuations in a time series. High value indicates that similar patterns are not followed by the same.	EMG signals are nonstationary signals that vary erratically with time. Such a time series signal is prone to fluctuations. Here we see if correct and incorrect exercises produce differentiable EMG in terms of predictability.
Mean Frequency	Mean-normalised frequency of the power spectrum of a signal.	Mean and median frequencies are useful in estimating muscle fatigue.
Median Frequency	Median-normalised frequency of the power spectrum of a signal.	Mean and median frequencies are useful in estimating muscle fatigue.
Largest Lyapunov Exponent	It quantifies the rate of divergence or convergence of close trajectories in phase space. +ve - divergence, -ve - convergence.	In the phase space, our goal was to analyse whether or not correct and incorrect exercises produce convergence/divergence for classification.
Kurtosis	Kurtosis is a measure of how outlier-prone a distribution is. The kurtosis of the normal distribution is 3.	In spite of outlier detection and removal, some outliers are inevitable in analysis. Our goal was to exploit that to see if this could be a suitable feature for analysis.

Results: Feature Extraction

```
Energy: 9.318309
Kurtosis: 3.034770
Power: -31.118966
Mean freq: 0.003440
Med freq: 0.000174
D_med: 0.049004
D_rms: 0.142134
Entropy: 62.196729
DFA: 0.679800
LLE: 187.777843
```

```
Energy: 3.683953
Kurtosis: 7.271742
Power: -34.887911
Mean freq: 0.006132
Med freq: 0.000190
D_med: 0.063790
D_rms: 0.091147
Entropy: 27.380331
DFA: 0.709350
LLE: 198.971243
```

Sample of extracted features for Exercise C: For correctly done exercise (left), for incorrectly done exercise (right)

SECTION-3:
Feature Selection

Algorithms used:

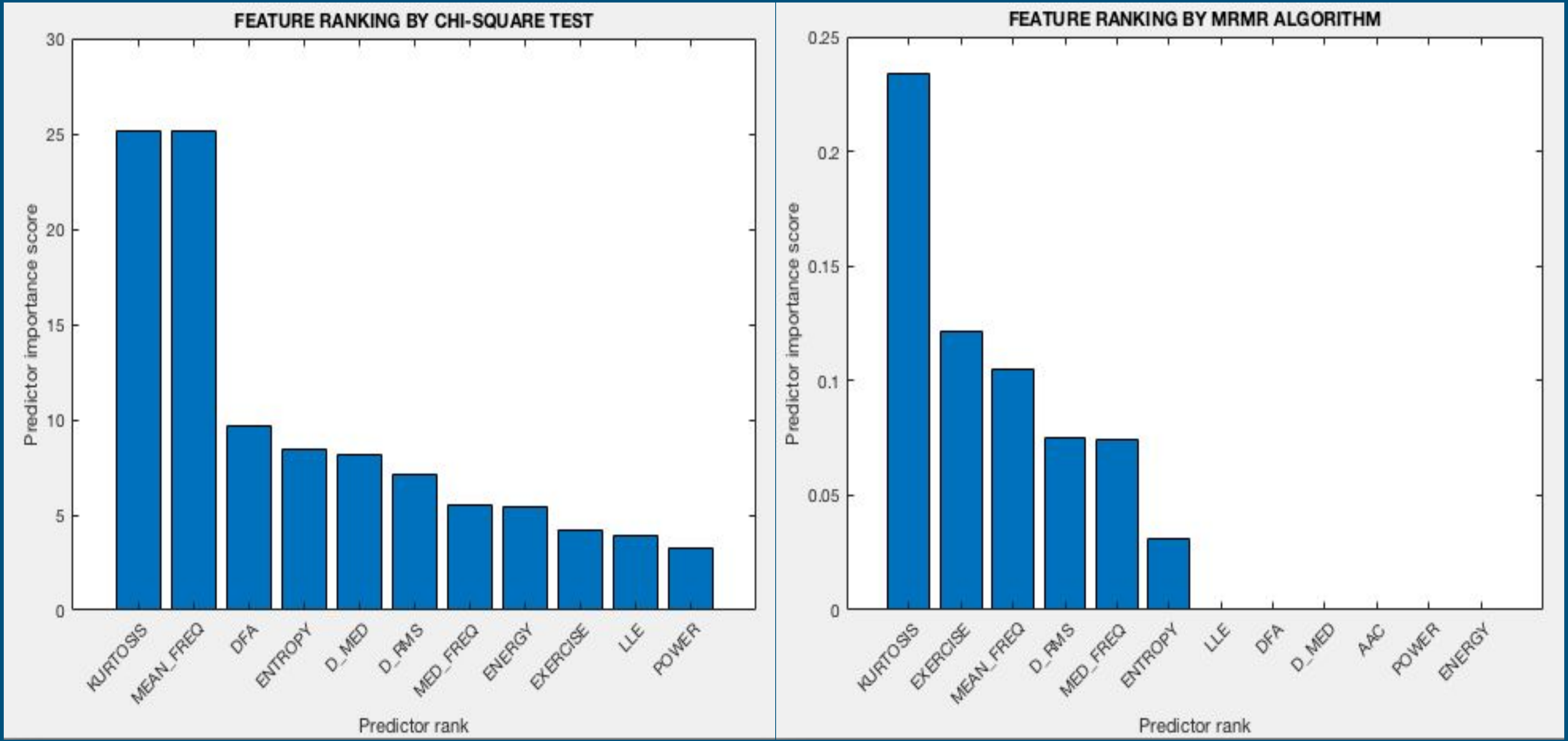
1. <u>Chi-square test:</u>

   Examines if each predictor is independent of its response variable using individual chi-square tests. A small p value indicates a large predictor importance score.

2. <u>MRMR algorithm: Minimum Redundancy Maximum Relevance</u>

   This algorithm picks the features that are mutually and most dissimilar from each other but can represent the response variable effectively. That is, it selects the features that have the highest correlation with a class (relevance) but the least correlation between themselves (redundancy).

Results:


FEATURE RANKING BY CHI-SQUARE TEST
Predictor importance score
0
5
10
15
20
25
30
KURTOSIS
MEAN_FREQ
DFA
ENTROPY
D_MED
D_RMS
MED_FREQ
ENERGY
EXERCISE
LLE
POWER
Predictor rank
FEATURE RANKING BY MRMR ALGORITHM
Predictor importance score
0
0.05
0.1
0.15
0.2
0.25
KURTOSIS
EXERCISE
MEAN_FREQ
D_RMS
MED_FREQ
ENTROPY
LLE
DFA
D_MED
AAC
POWER
ENERGY
Predictor rank

Selected features:

The selected features for the classifier are:

a. Kurtosis
b. Mean frequency
c. DFA - Hurst exponent
d. Entropy
e. D_med
f. Median frequency

SECTION-4: Classification - Training and Testing

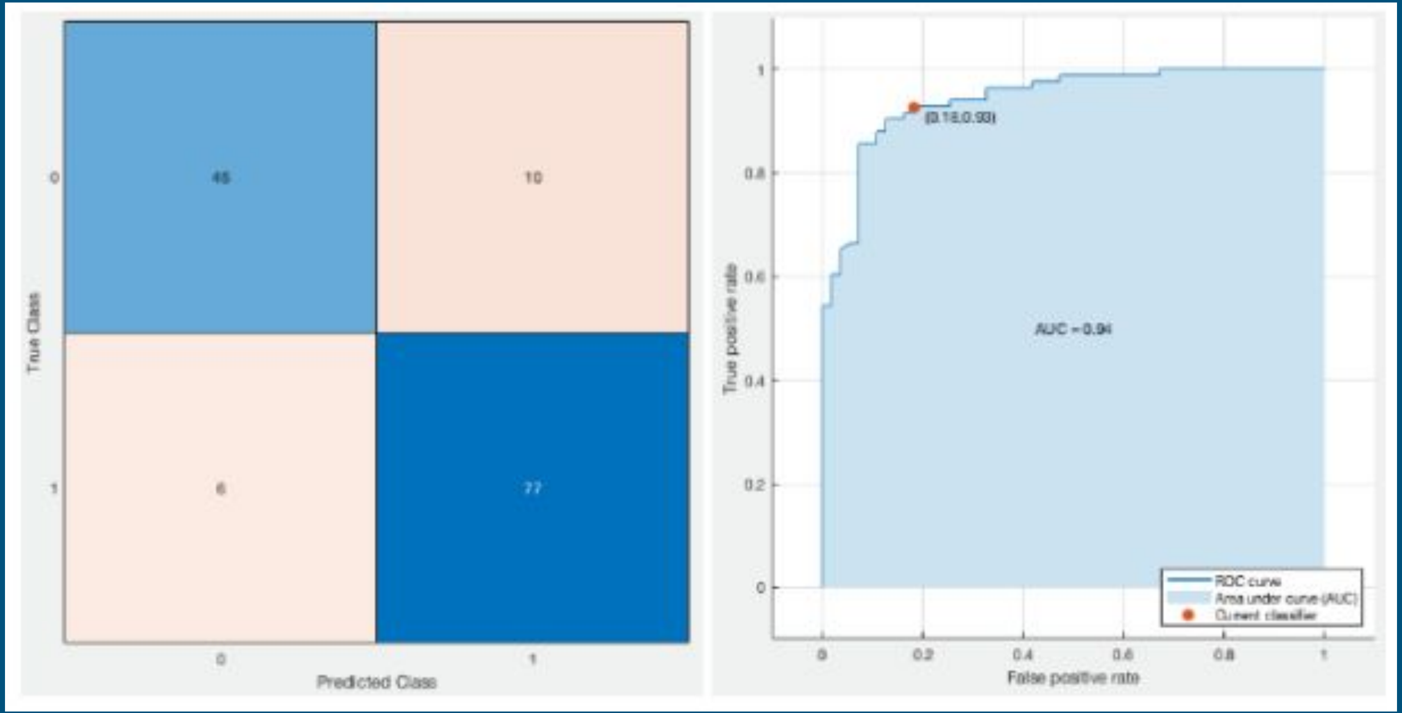
Ensemble Learning:

1. Ensemble Learning algorithms make use of multiple machine learning algorithms to classify. This is more robust than taking the results of a single classification algorithm.
2. In this project, bagging and boosting algorithms were used.
3. Bagging, AdaBoost, RUSBoost, LogitBoost and GentleBoost algorithms were employed for classification.
4. Their hyperparameters were tweaked and multiple trials were run to acquire the best possible classifier.

Results:

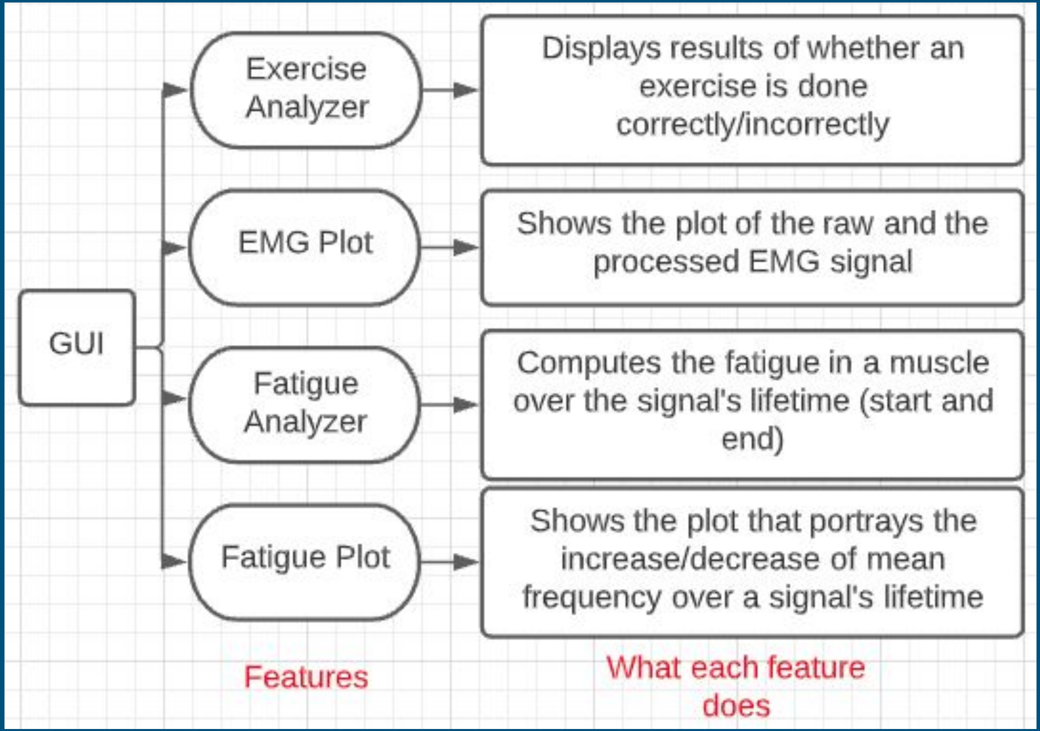
MODEL	PARAMETERS	TRAINING ACCURACY (%)	TESTING ACCURACY (%)
Bagging	20 splits, 5 learners, learning rate 0.1	97	84.6
AdaBoost	20 splits, 30 learners, learning rate 0.1	60.1	53.8
RUSBoost	20 splits, 30 learners, learning rate 0.1	100	76.9
RUSBoost	35 splits, 35 learners, learning rate 0.01	98.47	92.3
LogitBoost	20 splits, 25 learners, learning rate 0.01	94.9	84.6
GentleBoost	20 splits, 30 learners, learning rate 0.1	100	92.3

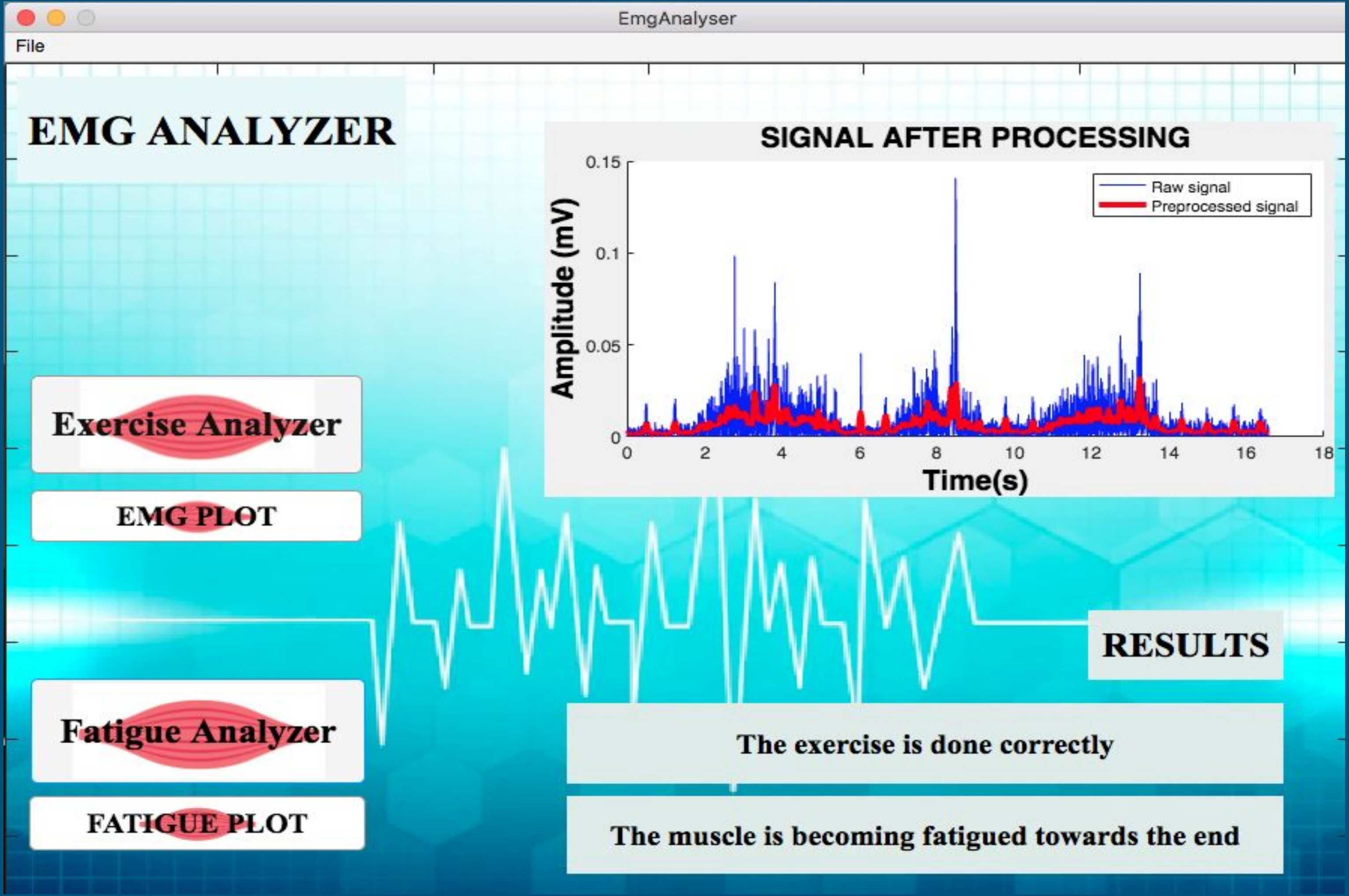
5-fold stratified cross-validation: AUC - 0.94



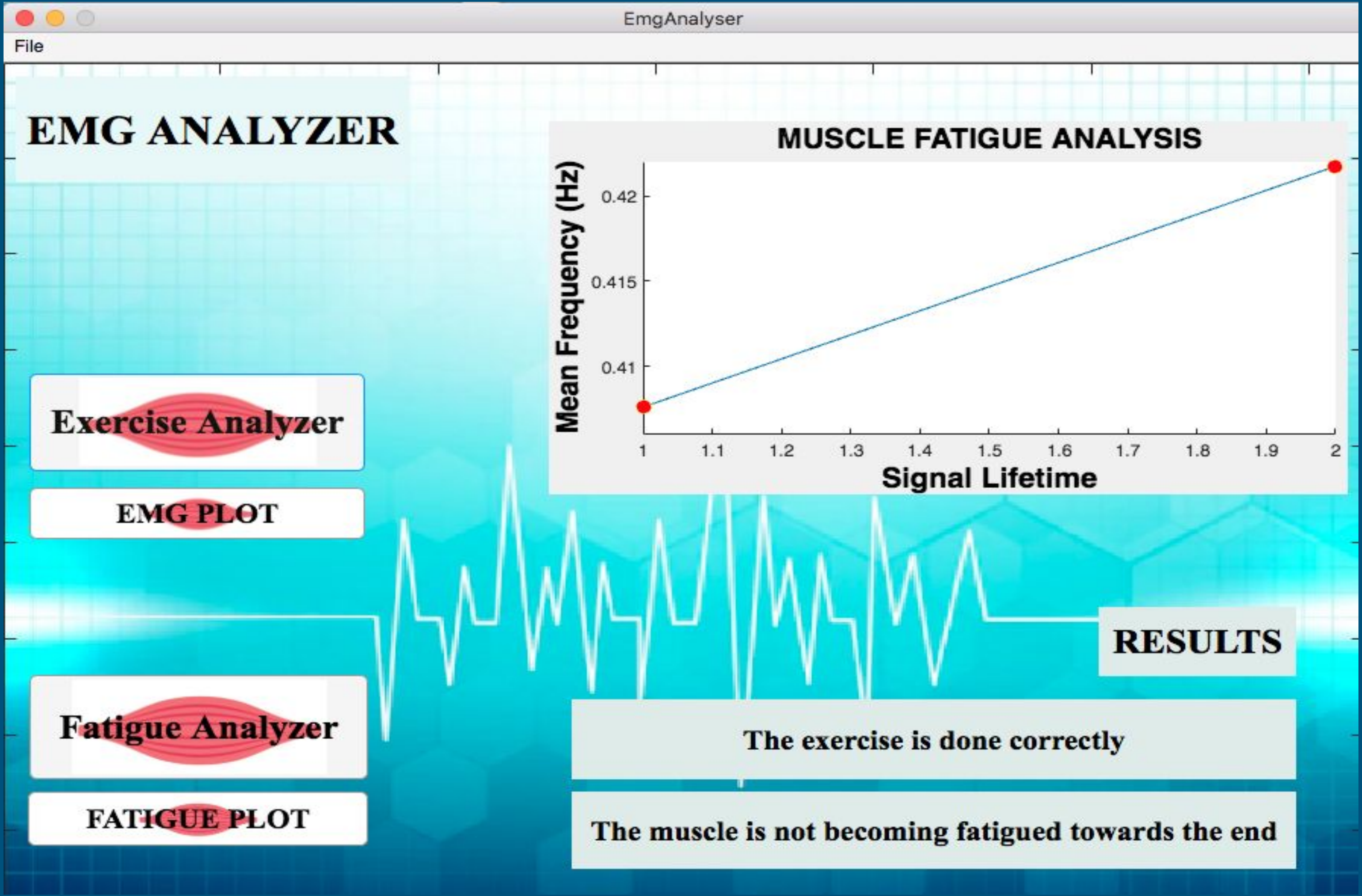
SECTION-5:
Graphical User Interface

Functions of the GUI:





View of the GUI : EMG Plot and EMG Analyzer



View of the GUI : Fatigue Plot and Fatigue Analyzer

SECTION-6: Conclusions and Discussions

Conclusions and key takeaways:

1. EMG signals are capable of classifying correctly and incorrectly done exercises.
2. Time-domain features were not very useful for classification, whereas features extracted from the other domains were.
3. Features ranked by the chi-square test algorithm worked better than those ranked by the MRMR algorithm. A combination of features from taken from both the algorithms after multiple trials.
4. RUSBoost and GentleBoost classifiers work best on the data. However, RUSBoost is better suited owing to its reduced computational complexity, computation time and also because the dataset is imbalanced.

   RUSBoost - 930 observations/second

   GentleBoost - 750 observations/second

5. The GUI has all the functionalities in it for extraction and classification and can be installed in any system easily. It is also easy to understand and requires no prior knowledge of signal processing or machine learning to operate and use.

Novelty in the project:

1. EMG signals have extensively been used to diagnose neuromuscular disorders and for automation. This project is a combination of how EMG signals can be used in the medical field while combined with automation.
2. Monitoring the patient’s gait and muscle fatigue are the most common applications of EMG signals in automation. In this project, we have worked on using these EMG signals for the real-time monitoring of patients who are undergoing physiotherapy.
3. EMG signals are a more quantitative way of differentiating between correctly done and incorrectly done exercises. An automated EMG analysis system is bound to have lesser flaws than a mere visual observation by a supervisor. Moreover, it would also decrease the workload of the medical practitioner.

Cost Analysis:

COMPONENT	COST
Disposable Surface EMG Sensor Electrodes	Rs. 800/piece
Embedded board - ADS1292R (24-bit ADC, 2-channel, with in-built PGA and DAQ)	Rs. 7593/board (USD 99)
TOTAL	Rs. 8393

Constraints, alternatives and trade-offs:

1. **Constraint:** Less number of datasets for other age-groups

   Alternatives: Amplitude-based feature extraction is reduced

   Trade-off: May not work as efficiently for other age-groups, but will work very well for modelled age-groups.

2. **Constraint:** Model has learnt only for some specific exercises.

   Alternatives: Exercise type as a predictor is avoided.

   Trade-off: Classifier may not work for exercises that need to be modelled separately, but is well-trained for the exercises it learnt

3. **Constraint:** Input can only be given in .mat format

   Alternatives: .csv files can be uploaded as a full dataset.

   Trade-off: Memory load of GUI will be increased, but there is no constraint on upload format

Future work:

1. More datasets can be acquired spanning different ages, genders and exercises. A more robust model can be trained separately for each of these cases.
2. Beyond muscle rehabilitation, EMG signals could also be processed to assess and diagnose any neurological disorders such as strokes, for real-time monitoring.
3. EMG signal processing can be integrated with other biosignal processing systems for overall health analysis while performing any exercise.

References:

[1] Taborri J, Keogh J, Kos A, Santuz A, Umek A, Urbanczyk C, van der Kruk E, Rossi S. Sport Biomechanics Applications Using Inertial, Force, and EMG Sensors: A Literature Overview. Appl Bionics Biomech. 2020 Jun 23;2020:2041549. doi: 10.1155/2020/2041549. PMID: 32676126; PMCID: PMC7330631.

[2] Vujaklija, I., Shalchyan, V., Kamavuako, E.N. *et al.* Online mapping of EMG signals into kinematics by autoencoding. *J NeuroEngineering Rehabil* 15, 21 (2018). https://doi.org/10.1186/s12984-018-0363-1

[3] Palumbo A, Vizza P, Calabrese B, Ielpo N. Biopotential Signal Monitoring Systems in Rehabilitation: A Review. Sensors (Basel). 2021 Oct 28;21(21):7172. doi: 10.3390/s21217172. PMID: 34770477; PMCID: PMC8587479.

[4] McManus, Lara, et al. “Analysis and Biophysics of Surface EMG for Physiotherapists and Kinesiologists: Toward a Common Language With Rehabilitation Engineers.” *Frontiers in Neurology*, vol. 11, no. 10.3389/fneur.2020.576729, 2020. *Frontiers*, https://www.frontiersin.org/article/10.3389/fneur.2020.576729.

[5] Kumar Samantaray, Aswini, and Priyanka Mallick. “Decision Based Adaptive Neighborhood Median Filter.” *Procedia Computer Science,*, vol. 48, 2015, pp. 222-227. *Science Direct*, https://www.sciencedirect.com/science/article/pii/S1877050915006833