# A Predictive model for the detection of Muscle fatigue using sEMG signal

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**Abstract**

Surface electromyography (sEMG) is an important dimension for analyzing exercise and muscle activity. sEMG requires a very high sampling rate, thus wireless transmission of generated signals becomes very challenging. An important application of sEMG monitoring is the detection of muscle fatigue. The present study proposes a novel framework for the detection of muscular fatigue by monitoring sEMG signals obtained from various muscle groups throughout the body. The system uses an LSTM predictive model for the binary classification of sEMG signals trained on the UCI dataset.

**Keywords**—Electromyography, sEMG, muscular fatigue detection, LSTM algorithm, deep learning, RNNs.

## 1. INTRODUCTION

Muscle fatigue arises due to the reduction in the ability of muscles to produce contractions [1]. This can be a result of vigorous physical exercise or neurological factors. The ability of muscles to produce contractions is limited by the ability of motor neurons in sustaining high frequency stimuli. Real-time monitoring of muscle fatigue demonstrates the biochemical and physiological changes during physical activity and acts as an excellent tool for performance analysis in sports and athletics [2].

Surface electromyography is an excellent method for non-invasive monitoring of muscular activity [3, 4]. It is very easy to set up and user-friendly due to its non-invasive nature. This has resulted in increased adoption in various biomedical applications [5, 6]. It is also used as an accessory for prosthetic limbs for various tasks such as movement recognition [7]. sEMG signals are highly compatible compared to other measurement techniques such as electroencephalograms and are ideal for the development of wearable electronic devices [8]. However, increased sensor noise and cross-talk may result in inaccurate analysis [9]. This is an important consideration while developing sEMG-based devices.

The sEMG signals are ideal for the continuous monitoring of muscular activity. They can be used for the detection of various muscular disorders and conditions. Detection of muscular fatigue provides significant insights for both clinical and performance athletics applications. The present study proposes a novel framework for the detection of muscular fatigue with the help of sEMG signal analysis.Surface electromyography can be used in combination with predictive algorithms such as neural networks to produce excellent results in terms of the detection of physiological events. The long short-term memory (LSTM) algorithm is a type of recurrent neural network widely used for processing large continuous sequences of data. The proposed system uses the LSTM predictive model trained on a 4-channel analog sEMG signal data log with a sampling rate of 1kHz called the UCI dataset for real-time detection of muscle fatigue using analysis of sEMG signals. The main objective of the study is the analysis of performance accuracy in the detection of muscle fatigue and the effect of the LSTM predictive model on real-time monitoring and response of the system.

Various researchers have reviewed the performance of intermittent RNN predictive models for anticipation of resting earthquake patterns in EMG signals [10]. EMG signals in combination with inertial measurement units (IMUs) are also used for kinematic analysis of gait parameters [11]. Performance analysis shows that LSTM models offer better results compared to SVM-based techniques [12].

Deep learning architectures have also been applied for multi-stroke handwriting sequence recognition using sEMG signal analysis acquired through a wristband monitoring device [13]. Studies also explore the application of sEMG signals in gesture recognition by utilizing spatial-temporal features of the perished signals [14]. Review studies also investigate the application of deep learning architectures in combination with an EMG-based human-machine interface for torque estimation in muscular activity [15]. Comparative studies of numerous adaptive algorithms suggest that the application of convolutional neural networks improves the performance of the system in terms of precision [16].

When it comes to data acquisition and pre-processing, various researchers propose techniques for multi-channel data acquisition of both synergistic and agonistic sEMG data. A multi-channel fusion RNN model as a predictive tool has also been proposed [17]. Inheritable programming methods for muscle fatigue detection using sEMG signal analysis have also been explored [18]. Some researchers propose the usage of deep belief networks (DBNs) as a literacy medium for the prediction of muscle fatigue onset from the upper extremities of the sEMG signal [19]. Denoising frameworks implementing convolutional algorithms in combination with graph neural networks for fatigue detection have also been proposed [20].

It is observed that among the various methods suggested for the detection of muscle fatigue using sEMG signal analysis, there is a lack of consideration of user information and the physical state of the user which is crucial for muscle fatigue detection. The lack of automated signal acquisition techniques and devices also hinders implementation.

## 2. METHODOLOGY

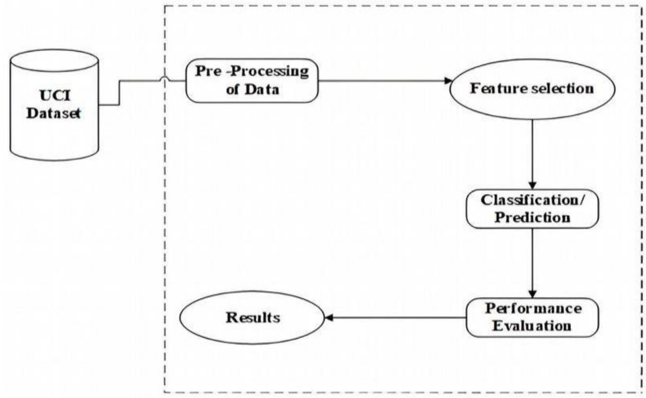



Fig. 1. Brief overview of the proposed solution.

Fig. 1 describes the various processes involved in muscle fatigue detection using the LSTM predictive model. The algorithm is trained on the UCI sEMG dataset which contains 4-channel analog sEMG signals from 22 test subjects with 11 different conditions and a total of 67 readings. The data is acquired using an MWX8 data logger. The raw data undergoes pre-processing and the one-hot encoded data is subjected to feature selection to ensure dimensionality reduction. The obtained samples are used for training the LSTM model. The trained model is evaluated using various parameters.

### *A. Data Pre-Processing and Feature Extraction*

A total of five attributes are considered for training the model – Recto Femoral (RF), Femoral Biceps (BF), Vatus Medialis (VM), Flexion at the knee, and Semitendinosus (ST). The three factors that are to be considered for feature extraction are - segment (which defines the part of the body where data is acquired), channel (which corresponds to the electrode attached), and the muscle being measured.

TABLE 1. SELECTED FEATURES

| Segment | Lower Limb | | | | |
|---|---|---|---|---|---|
| Channel | Ch1 | Ch2 | Ch3 | Ch4 | Ch5 |
| Muscle | RF | BF | VM | ST | FX |
| Column | 0 | 1 | 2 | 3 | 4 |

Table I shows the channels, muscle groups, and segments selected for analysis. Muscle fatigue in the lower limbs using 5-channel measurements has been considered.

The original UCI sEMG dataset contains 67 samples with labels – fatigue detected and normal. Out of these 67 samples, 9 samples were found to have missing values. Such samples were eliminated and a total of 58 sEMG samples were considered for training the LSTM predictive model. Thus, a total of 4 electrodes with 5 shares or motion repetitions were considered for each subject.

The obtained data is stored in four folders - A_LOG, A_TXT, N_LOG Y N_TXT. Folder _log contains data in .log format that can be loaded and analyzed by the data log software. Folder _txt contains SEMG data in columns and their headers.

TABLE 2. CONTENTS OF A STANDARD FOLDER

| Channel | Muscle | Values | Units | Filter Used |
|---|---|---|---|---|
| Ch1 | RF | 15300 | mV | No |
| Ch2 | BF | 15300 | mV | No |
| Ch3 | VM | 15300 | mV | No |
| Ch4 | ST | 15300 | mV | No |
| Ch5 | FX | 765 | degrees | No |

*Channel – 5 is extrapolated from 50 samples to 1000 samples per second

A sample folder 2Nsen.log contains data from five channels as shown in Table II.

Fig.2. Pre-processed sEMG signals from Ch-1 .

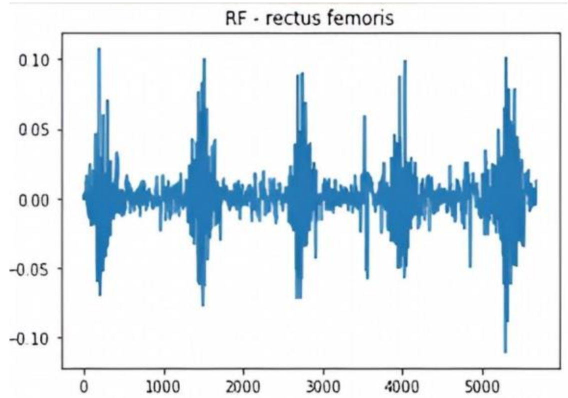
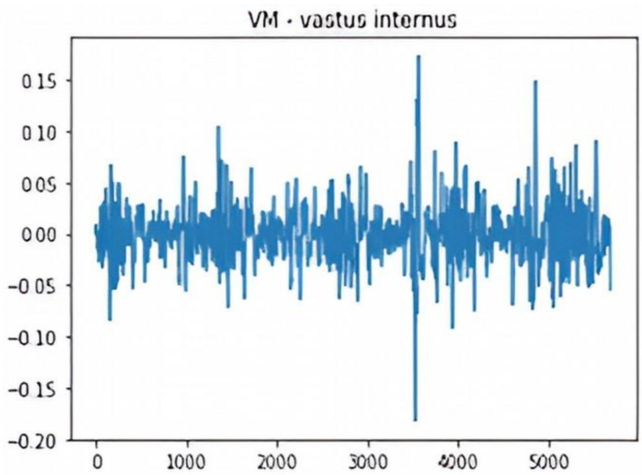



Fig. 3. Pre-processed sEMG signals from Ch-3 .

Fig.2 and Fig. 3 represent the conditioned signal samples obtained. The waveforms describe the magnitude of sEMG signals during continuous motion repetitions for five cycles for various muscle groups.



### *B. Model Training*

The filtered and conditioned sEMG signals from the UCI dataset are used for training the LSTM predictive model. The channel labels from the '.txt' folders are converted into one-hot encoded arrays. The predictive model analyzes the sEMG signal sequences and outputs the one-hot encoded label array which classifies the signal into two classes – Normal and Fatigue Detected.

The optimization problem boils down to a univariate binary classification problem. The dataset is bifurcated into two subsets – the training subset and the testing subset. The model is trained for 300 epochs with an early stopping algorithm. Hyper-parameter fine-tuning is performed to optimize the learning rate of the algorithm.

The trained model is evaluated on the test subset based on various parameters. The obtained models are selected based on the accuracy of prediction. The selected model is stored in a '.h5' format for further implementation.

## 3. SYSTEM DESIGN

The design of a feasible system is an important requirement for real-time operation. Various sub-systems are recognized based on the construction modeling outlines which are portrayals of the product structure planning.

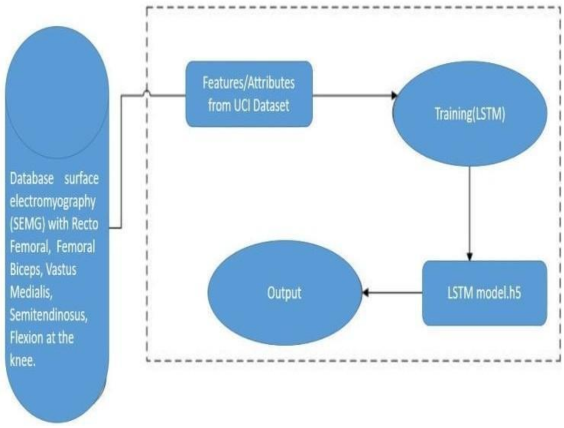



Fig. 4. Flow diagram of the system architecture.

Fig.4 provides a brief understanding of the system components and the working of the proposed architecture. The input signals are subject to feature extraction and are fed as the input to the trained LSTM predictive model. The model analyzes the sEMG sequence and outputs the classification label.

### *A. Data Flow Diagram and its Components*

The data flow diagram provides an overview of the logical flow of information across the system architecture. It also establishes the required notations and determines the physical requirements for real-time operation. The data flow diagram representing the source, destination, and data storage mechanisms can be broken down into four components – entities, process, data storage and data flow. Entities refer to the components which act as data sources or receive outputs from the system. Processes refer to the logical and computational operations which are performed to extract inferences from the input data. Data storage refers to folders or repositories which store information for further use or analysis. Data flow refers to the route taken by the data stream from the input to output.

The architecture can be broken down into two layers – level-0 and level-1. Fig. 5 and Fig. 6 describe the data flow for level-0 and level-1. Level-0 deals with data pre-processing and one-hot encoding of the generated feature vector. Level-1 deals with training and selection of the optimized predictive model, results from the analysis, and the display of results.

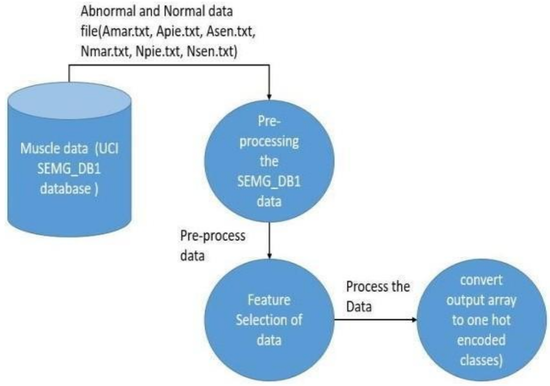



Fig. 5. Data flow diagram for level-0.

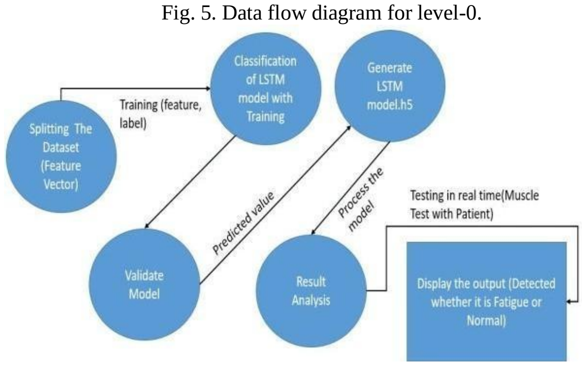



Fig. 6. Data flow diagram for level-1.

### *B. Case and Sequence Diagrams*

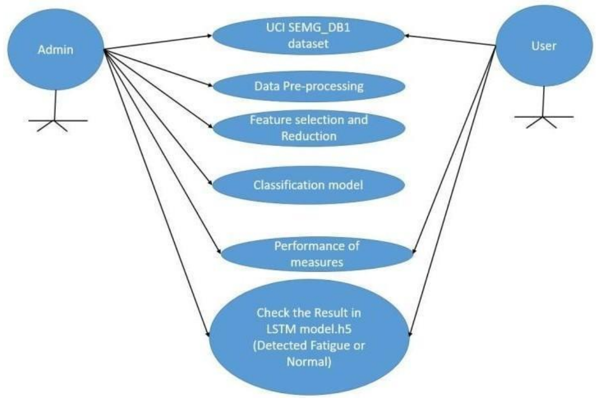



Fig. 7. Case diagram of the model.

Fig. 7 describes the functional requirements of the system and provides an outside view of the system. It is useful for the determination of internal and external influencing factors. It also provides information regarding the interaction between various components of the system.

Sequence diagrams provide information on the various processes involved, their operations, and outcomes arranged in sequential order. The Exchange of messages between various components and the response of the system to different scenarios can be analyzed with the help of the sequence diagram. The representation and study of the case and sequence diagrams provide useful insights into the real-time operation of the system and are useful for gauging the design of the architectural components and their order.

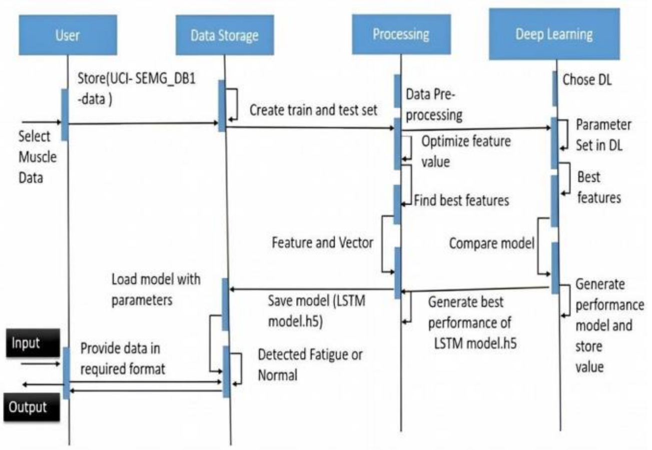



Fig. 8. Sequence diagram of the model.

Fig. 8 provides information regarding the logical flow of data and interaction between various individual components of the system as discussed earlier.

## 4. RESULTS AND DISCUSSIONS

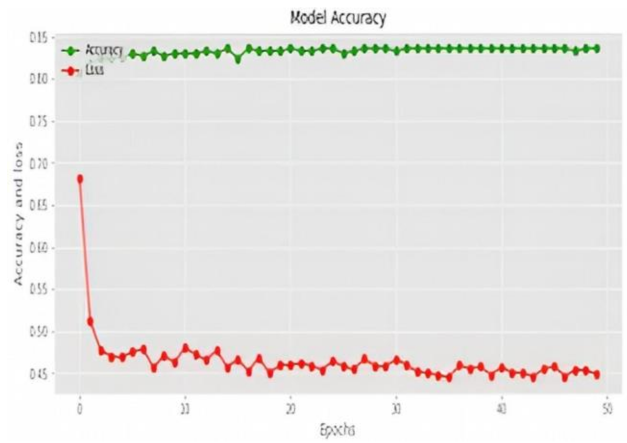



Fig.9. Training curves and confusion matrix.

The performance of the muscle fatigue detection system is evaluated on the test subset obtained from the UCI sEMG dataset using a test train split of 80:20. The optimal model is selected based on error minimization and accuracy. Other parameters such as validation curves and confusion matrix have also been considered for further evaluation.

An accuracy of 84% was obtained on the test subset. The system provides an efficient real-time diagnosis of muscle fatigue. The results obtained are very useful for the detection of muscular abnormalities. The detailed analysis of the trained model has been presented in Fig. 9 and Fig. 10. The framework is ideal for use in clinical environments and also has applications in athletic performance analysis. The algorithm can also be incorporated into a mobile application for increased ease of use and monitoring by the patients and medical professionals. This provides a broader perception of significant features for muscle fatigue detection.


Fig.10. Confusion matrix of the trained model.

## FUTURE WORKS

The research can be extended to hardware implementation of sEMG-based data acquisition systems. Also, domain specific applications related to athletic performance analysis and biomedical applications can be discussed in detail. Biometric applications such as handwriting analysis can be explored.

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