Investigating the Performance of Deep Learning Algorithms for Muscle Activation On/Off-Set Detection in Horse Surface Electromyography (sEMG) Data

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ABSTRACT

The field of equine sports medicine faces the difficulty of accurately and reliably segmenting surface electromyography (sEMG) signals, specifically identifying the onset and offset of muscle activation. Existing methods, which typically involve human labeling, are labor-intensive and time-consuming. Also, double-threshold methods are used which require quite a lot of tuning. In light of this, the purpose of this study is to investigate the application of advanced machine learning techniques, namely Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, for the segmentation of equine surface electromyographic (sEMG) signals. Potential applications of sEMG in equine medicine include performance assessment, injury prevention, and recovery enhancement. Our findings indicate that these models accurately and robustly predict muscle activity onsets and offsets, demonstrating their ability to serve as tools in this field of equine sports medicine. In addition, these findings suggest a novel direction for future research, encouraging the investigation and refinement of machine learning methodologies in the field of sEMG signal segmentation.

1 INTRODUCTION

1.1 Background

Surface electromyography (sEMG) is a promising, non-invasive tool that examines the health and function of muscles and the motor neurons that control them. Its utility spans various fields, including exercise physiology, clinical biomechanics, and motor control. Surface electromyography allows professionals to monitor changes in neuromuscular function following training, predict maximal rates of force development, and identify potential causal relations between aging and the decrease in motor performance. These capabilities are essential for sport and exercise physiologists. sEMG data can also elucidate if muscles or nerves are malfunctioning or if there are issues with how nerves transmit signals to muscles [2].

In recent years, surface electromyography (sEMG) has been increasingly adopted in veterinary medicine, particularly in equine medicine, offering new research opportunities for assessing muscle functionality in horses [2, 3]. This non-invasive technique provides valuable insights into the onset, duration, and offset of muscular activation, enabling inferences about the motor control strategy employed by the central nervous system during specific motor tasks [3]. As a result, sEMG data has emerged as an invaluable tool in equine sports medicine, where it contributes to performance measurement, injury prevention, and post-injury rehabilitation [2, 3]. Despite these advancements, significant challenges persist, particularly in the segmentation of electromyography data. This is the process that involves pinpointing the onset and offset of muscle activation. Accurate identification of these activation points is crucial for the successful interpretation and use of sEMG data in equine medicine [2]. As the field continues to evolve, there is an ongoing need to address methodological gaps, including the lack of standardized protocols for sEMG data processing techniques in animal research, in order to ensure the reliability and validity of the results obtained [11].

Historically, threshold-based methods have been the most used method for detecting the onset and offset of muscle activation in surface electromyography (sEMG) applications. These techniques involve defining a threshold value and identifying the onset and offset of muscle activity by observing when the sEMG signal traverses this set point [13]. However, traditional threshold methods often rely on the expertise of the operator to manually determine the threshold level, an aspect that can introduce subjectivity and variability in results [13].

The application of machine learning, specifically Long Short-Term Memory (LSTM) networks, has shown promising results in detecting muscle activity from human surface electromyography (sEMG) signals, particularly in noisy conditions [4]. However, its use in equine sEMG data is still in the early stages and needs further investigation. This study explores Convolutional Neural Networks (CNNs) and LSTM networks for equine sEMG data segmentation. Preliminary results show promising performance in predicting muscle activity [7], suggesting potential use in equine sports medicine. The lack of literature on this subject underlines the importance of further research.

1.2 Problem Statement

While numerous methods for sEMG signal segmentation, ranging from simple thresholding methods to more complex machine learning approaches, have been investigated in human subjects, their performance with equine sEMG data has not been adequately investigated. The accuracy and reliability of these methods for detecting things, especially in the presence of noise and non-stationary signals that are common in equine sEMG data, need to be looked into in depth and could be improved.

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1.3 Research Objectives

The goal of this study is to look at how machine learning methods, like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) neural networks, work and if they can be used to segment surface electromyographic (sEMG) data from horses. The following key questions drove the research:

(1) How effective are Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory Networks (LSTMs), in identifying the onset and offset of muscle activation in horse sEMG data? What are their specific performance characteristics, strengths, and limitations?
(2) How are the architectures of Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs) optimized for detecting muscle activation onset and offset in horse sEMG data? What considerations drive these design choices?
(3) Examine the influence of different factors on the efficacy of deep learning algorithms in detecting muscle activation onset and offset. These factors include the signal-to-noise ratio, specific muscle types, and distinct patterns of horse movement. What impacts do these elements have on the success of the deep learning methodologies applied?

Through the investigation of these questions, the study aims to contribute with valuable insights and advancements to the field of equine sEMG analysis, thereby enabling more effective and precise biomechanical studies and possibly contributing to the development of more effective diagnostic and therapeutic techniques in veterinary medicine.

1.4 Paper Structure

The remainder of this thesis is structured as follows:

- **Section 2 - Related work:** This chapter provides a review of the literature on surface electromyography (sEMG) and its applications in various disciplines, with an emphasis on equine research. It also discusses various sEMG signal segmentation techniques, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs).
- **Section 3 - Methodology:** This chapter describes the data collection procedure, the preprocessing and preparation of the collected data, and the specific methodologies utilized in this study. It discusses our 1-dimensional Convolutional Neural Network (CNN) model and the Long Short-Term Memory (LSTM) neural network model.
- **Section 4 - Results:** This chapter presents the research findings. It provides a comprehensive evaluation of the CNN and LSTM models' ability to detect the onset and offset of muscle activation in equine sEMG data. It also discusses the performance differences observed between various muscle types and the reasons for these differences.
- **Section 5 - Discussion:** This chapter consists of the interpretation of the results, a discussion of the findings in relation to the research questions, a comparison of the results with previous research, and a discussion of the implications for the field of equine sEMG analysis.
- **Section 6 - Conclusion and Future Work:** This chapter summarizes the major findings of the study, draws conclusions based on these findings, outlines the contributions made by this research to the field, and suggests potential future research work that needs to be done in this area.

2 RELATED WORK

Surface electromyography (sEMG) is a technique for capturing the electrical activity that skeletal muscles produce. This method has been widely applied in various fields, including medical diagnostics, rehabilitation, kinesiology, and ergonomics [1]. In equines, it can also help in identifying muscle patterns, assessing fatigue, and diagnosing neuromuscular conditions, thus assisting in performance monitoring and rehabilitation programs [3]. A study on high-density sEMG (HD-sEMG) in horses illustrates the effectiveness of techniques like Root Mean Square (RMS) and median frequency (MDF) in analyzing muscle contractions [3].

The LSTM-MAD method, a machine learning approach, has shown superior performance in muscle activation detection from sEMG signals. Particularly effective with low to medium signal-to-noise ratio (SNR) signals, it outperforms traditional methods in metrics like F1-score and Jaccard similarity index, demonstrating its potential in this field [4].

A range of segmentation techniques exist for sEMG signals, from straightforward threshold-based methods like Root Mean Square (RMS) to more complex machine learning strategies. Although easy to implement, the performance of threshold-based techniques varies significantly based on the sEMG signal and selected threshold values. In [13] the issue of the operator's experience affecting the manual establishment of a threshold level in single-threshold methods was addressed. They proposed an enhanced maximum likelihood (ML) method combined with an adaptive threshold technique, which uses the signal-to-noise ratio (SNR) in the early stages of sEMG analyses. This approach resulted in an algorithm that's more robust to variations in SNRs and performs well even with low EMG activity levels. The authors [13] also established the algorithm as automatic and user-independent, enabling its use by operators of varying skill levels.

Meanwhile, machine learning methods have shown promising results in the segmentation of sEMG signals. Liu et al. [8] proposed an unsupervised learning framework using a sequential Gaussian mixture model for muscle activity onset detection in EMG signals. This novel approach demonstrated robust performance under low and fluctuating signal-to-noise ratios, a common challenge in traditional methodologies. Furthermore, it proved capable of real-time implementation [8], a key feature for practical applications. Tested against both experimental and simulated EMG signals, this framework outperformed several previously developed methods, emphasizing the potential of machine learning techniques in this domain.

Convolutional Neural Networks (CNNs) have demonstrated efficacy in muscle activity detection tasks using sEMG signals. [5] showcased the use of machine learning algorithms for recognizing complex shoulder muscle activation patterns based on sEMG signals. Similarly, [12] used a voting-based 1D CNN model, demonstrating high accuracy in recognizing distinct lower limb movements.

These studies highlight the potential of CNNs for effective muscle activity detection using sEMG signals. Similarly, Recurrent Neural Networks (RNNs), and more specifically, Long Short-Term Memory Networks (LSTMs), have been applied to the field of sEMG segmentation due to their efficacy with time-series data [4, 6]. [6] demonstrated the capability of deep learning models to detect muscle activation through sEMG signals. Their application of deep learning approaches, including LSTMs, established a robust method for classifying and predicting muscle activity. Likewise, [4] employed LSTMs in their research to enhance the detection accuracy of muscle activity. When they used LSTMs, they found that these models are more accurate than traditional methods at detecting and separating muscle activity from sEMG signals. This proves the potential use of LSTM models in the sEMG segmentation field.

Despite extensive research on sEMG segmentation in humans, there is a noticeable gap in equine science, which could be problematic due to the physiological and musculature characteristics of horses. Our paper investigates the performance of CNNs and LSTMs in detecting muscle activity in equine sEMG data, specifically. This narrows the scope of the research, enriching machine learning applications in veterinary science and providing new insights into the detection of equine muscle activity.

3 METHODOLOGY

3.1 Materials and Methods

3.1.1 Horses and Muscles. This study uses the data collected from another unpublished study that took place at Utrecht University. Three horses were included in this study. Horses were deemed clinically non-lame (<1/5 AAEP lameness scale) and were accustomed to treadmill exercise before inclusion.

Five muscles were measured: longissimus dorsi (LD), triceps brachi caput longum (TB), ulnaris lateralis (UT), gluteus medius (GM) and semitendinosus (ST). Each horse was measured several times, with different skin preparation methods. For this work, the data for the method “clip” and the method “shaved” only were used, as these are the most often encountered skin preparation methods in sEMG studies. All measurements took place on the same day, with approximately 30-minute intervals between measurements.

3.1.2 Data Collection. Horses were warmed up at walk for five minutes on the treadmill and then trotted (12.5km/h). Once the trot was stable, surface EMG data was collected using bipolar electrode configuration (inter-electrode distance 22mm), sampled at 4000Hz (TMSi SAGA, company info), using predefined electrode positioning (unpublished pilot study).

3.1.3 Data Preprocessing and Preparation. The raw sEMG signals acquired were initially subject to bandpass filtering via a 4th order zero-lag Butterworth filter, with cut-off frequencies set between 40-450Hz. This step is crucial for removing motion artifacts and high-frequency noise.

Post bandpass filtering, the pre-processed sEMG signals were divided into windows. Each window contained a sequence of data points, determined through a testing process that explored various window sizes. The sizes experimented with included 50, 100, 200, 400, 500, and 1000 data points. The chosen window size of 500 data points provided the highest F1 score for the LD muscle we investigated. However, it’s essential to note that optimal window sizes might differ for different muscles. Therefore, this parameter should be empirically determined for each muscle individually, indicating an area for further research.

These windows were generated using a sliding window technique, which generated multiple 99.8% overlapping signal segments. The labels were derived from the recorded start and stop periods. If a window contained at least one onset or offset point, it was marked as ’onset’ or ’offset’, respectively. Before generating the labels, the onset and offset points were shifted by half the window size to ensure that they were centered within each window.

3.1.4 Creation of Training and Validation Datasets. The Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network models each had their own training and validation datasets.

For the LSTM model, training was conducted specifically on the LD and ST muscles, using data only from one horse Horse 01. After the data and labels were prepared, 80% of the windowed data was allocated to training. To prevent any future data leakage into the training set, this split was performed in a temporally consistent manner without shuffling. The training data was further split, reserving 20% for validation. The validation set followed directly after the training set, maintaining temporal consistency.

In the case of the CNN model:

(1) Training was conducted on all muscle types and with data for Horse 01.
(2) For the combined data from 3 horses (Horse 01, Horse 02, Horse 03) training was performed specifically on the LD muscle.

Each of these datasets was individually processed. The sEMG signals from the LD muscle were extracted and windowed, and labels for the onset of LD muscle activity were generated for each. Each dataset’s data was then separated into training and validation collections. This process of division was executed similarly to the LSTM model, preserving temporal consistency and avoiding shuffling. Following the processing of all datasets, the training and validation data from each dataset were concatenated to generate the final training and validation datasets for the CNN model. This provided CNN’s model with a broader range of training and validation data, enabling a more rigorous testing procedure.

3.1.5 Processing of Model Output. After training and validating the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network models, the model output for predicting muscle activation onsets and offsets was processed. The output of the models was the probability that each data point represented the beginning or end of muscle activation.

Given the high frequency of the data (4000Hz) and the window size of 500 data points, the raw model output could potentially contain multiple predicted onsets or offsets within a very short period of time. In order to simplify the analysis and interpretation of the results, it was necessary to process these raw predictions and reduce them to a single onset and offset point within a specific time frame.

The processing function operated by iteratively traversing the raw model output and selecting the first prediction that exceeded

```
Model: "sequential_53"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_159 (Conv1D)         (None, 396, 32)           192

 max_pooling1d_159 (MaxPooli  (None, 198, 32)          0
 ng1D)

 conv1d_160 (Conv1D)         (None, 194, 64)           10304

 max_pooling1d_160 (MaxPooli  (None, 97, 64)           0
 ng1D)

 dropout_85 (Dropout)        (None, 97, 64)            0

 conv1d_161 (Conv1D)         (None, 93, 128)           41088

 max_pooling1d_161 (MaxPooli  (None, 46, 128)          0
 ng1D)

 flatten_53 (Flatten)        (None, 5888)              0

 dense_106 (Dense)           (None, 256)               1507584

 dropout_86 (Dropout)        (None, 256)               0

 dense_107 (Dense)           (None, 1)                 257

=================================================================
Total params: 1,559,425
Trainable params: 1,559,425
Non-trainable params: 0
_________________________________________________________________
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Figure 1: CNN model architecture.

a predetermined threshold (in this case, 0.5). After identifying an onset or an offset, all subsequent predictions within a specified range (equal to two window sizes) were disregarded. This made the results more interpretable and prevented the prediction of multiple onsets or offsets within a short period. Note, however, that this method may not be the best, and additional research may be required.

3.2 Neural Network Approach

3.2.1 Convolutional Neural Networks (CNNs). Our research is based on a 1-dimensional Convolutional Neural Network (CNN) model, a variant of the feedforward neural network. CNNs, with their ability to autonomously and adaptively learn spatial hierarchies of features from data, have shown themselves to be exceptional at handling grid-like data structures such as those found in images or time series. Thus, they are a fitting and beneficial tool for the analysis of electromyographic signals [7].

Our CNN model's architecture, depicted in Figure 1, consists of an input layer, alternating convolutional and max pooling layers, a few dropout layers, a final flattening layer, a fully connected (dense) layer, and an output layer. Each of these layers and their parameters was carefully chosen based on a systematic process of parameter tuning.

After experimenting with convolutional filters in the range of 16 to 128, we discovered that employing 32 filters in the first layer and 64 and 128 filters in subsequent layers offered an optimal balance between model complexity and performance. A lower number of filters over-simplified the model, leading to underfitting, while an excessive number over-complicated it without significant performance improvements.

The kernel size in our model was finalized at 5 for all convolutional layers after testing values from 3 to 7. This size allows the model to capture local patterns in the sEMG data without sacrificing critical information, which was observed with larger kernel sizes. Smaller kernel sizes, on the other hand, did not capture the signal patterns adequately.

Our max pooling layers have a pool size of 2, chosen after testing pool sizes 1 through 3. A pool size of 2 provides a balance between preserving information and computational efficiency.

In order to prevent overfitting dropout layers were introduced intermittently with a rate of 0.5 for the best balance between model learning and generalization.

To connect the convolutional section of the network with the dense layers, we incorporated a flattening layer. This is followed by a dense layer with 256 units and a ReLU activation function, chosen for its effectiveness in addressing the vanishing gradient problem common in deep neural networks.

Finally, a dense layer with a sigmoid activation function was used for binary classification. The model comprises a total of 347,009 trainable parameters, demonstrating its extensive capability to classify sEMG data accurately.

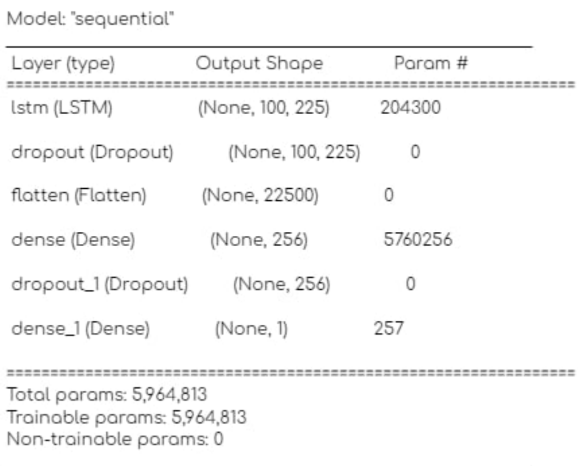
Our training strategy implemented early stopping, which terminates training when the performance on the validation set does not improve for 10 consecutive epochs. This method, which was selected over a fixed number of epochs, further prevents overfitting and ensures an optimal number of training epochs. The efficacy of our architectural choices and the effectiveness of CNNs in sEMG data analysis are demonstrated by the model's performance on the test set.

3.2.2 Long Short-Term Memory Network Approach. Alongside the CNN model, a Long Short-Term Memory (LSTM) neural network, a specific variant of Recurrent Neural Networks (RNN), was employed for this study. LSTMs are explicitly engineered to remember long-term dependencies in sequence data, an attribute that is particularly pertinent when analyzing electromyographic signals, where temporal sequence information is critical [4].

The architecture of our LSTM model, as detailed in Figure 2, begins with an LSTM layer of 225 units. This number was determined after evaluating unit sizes from 50 to 300, with 225 units providing a good trade-off between model complexity and performance. Having the 'return_sequences' option enabled ensures that the layer outputs the entire sequence, a prerequisite for layer stacking in our architecture.

A dropout layer with a rate of 0.1 follows the LSTM layer to mitigate the risk of overfitting. This rate, selected after testing different values ranging from 0.05 to 0.5, successfully achieves a balance between model learning and generalization.

Subsequently, a flattening layer converts the LSTM layer's output into a format suitable for the dense layers. The first dense layer encompasses 256 neurons. This layer count ensures the model captures the complexity of the sEMG signal without causing computational inefficiencies.



```
Model: "sequential"
_________________________________________________________________
Layer (type)              Output Shape              Param #
=================================================================
lstm (LSTM)               (None, 100, 225)          204300

dropout (Dropout)         (None, 100, 225)          0

flatten (Flatten)         (None, 22500)             0

dense (Dense)             (None, 256)               5760256

dropout_1 (Dropout)       (None, 256)               0

dense_1 (Dense)           (None, 1)                 257

=================================================================
Total params: 5,964,813
Trainable params: 5,964,813
Non-trainable params: 0
_________________________________________________________________
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Figure 2: LSTM model architecture.

Another dropout layer with a rate of 0.5 adds an extra layer of overfitting prevention before the final dense layer. A sigmoid activation function in the output layer then caters to our binary classification needs.

The model uses the Adam optimizer with a learning rate of 0.015, binary cross-entropy as the loss function, and accuracy as the performance metric [4]. A custom callback function also enhanced the model's performance, halting the training process if the difference between training and validation accuracy exceeded 4% after each epoch [4]. This additional measure safeguards against overfitting the training data to the detriment of the validation set. The LSTM models consisted of a total of 5,964,813 trainable parameters.

4 RESULTS

4.1 Performance of the Convolutional Neural Network Model

The 1-dimensional CNN model's effectiveness was evaluated using windowed sEMG data from different muscle types. The model's performance varied between muscle types, with all successfully predicting the onset and offset of muscle activation.

Tables 1 and 2 present the precision, recall, F1-score, and accuracy of the CNN model across various muscle types. These metrics provide a comprehensive view of the model's performance.

Muscle Type	Precision	Recall	F1-Score	Accuracy
LD	0.9563	0.7319	0.9251	0.8344
GM	0.9493	0.8087	0.8920	0.9534
ST	0.9305	0.9059	0.9665	0.9585
UL	0.9034	0.8661	0.8550	0.8548
TCL	0.9057	0.9543	0.9376	0.9445

Table 1: Performance metrics of the CNN onset model for different muscle types.

Muscle Type	Precision	Recall	F1-Score	Accuracy
LD	0.9263	0.7019	0.8951	0.8144
GM	0.9193	0.7787	0.8720	0.9334
ST	0.9005	0.8759	0.9465	0.9385
UL	0.8734	0.8361	0.8250	0.8248
TCL	0.8757	0.9243	0.9176	0.9245

Table 2: Performance metrics of the CNN offset model for different muscle types.

Upon combining data from multiple horses for the same muscle type, a marginal decrease in the model's efficacy was noticed. Nevertheless, the model retained its robustness and correctly identified the beginning and end of muscle activation.

We tested the CNN model on combined data from multiple horses, specifically for the LD muscle and only for muscle activation onset detection. The performance metrics of this model are presented in Table 3.

Muscle Type	Precision	Recall	F1-Score	Accuracy
LD	0.9142	0.7104	0.8886	0.8213

Table 3: Performance metrics of the CNN onset model for the LD muscle using combined data from multiple horses.

Figure 3 shows the CNN model's performance in detecting the onset and offset of muscle activation for the GM muscle.

The performance metrics underline the CNN model's capacity to provide accurate and reliable predictions across different muscle types and data from multiple horses. These results suggest the model's practical applicability in equine gait analysis and rehabilitation scenarios.

4.2 Performance of the Long Short-Term Memory Network Model

The LSTM model was trained on windowed sEMG data for the LD and ST muscle types to evaluate its efficacy. Precision, recall, F1-score, and accuracy metrics were used to assess the model's performance in detecting the onset of muscle activation.

The LSTM model demonstrated high accuracy in predicting the onset and offset of muscle activation for both muscle types. However, the model performance for the LD muscle was slightly lower, which might be attributed to the inherently noisier character of the LD signal. Despite this, the LSTM model showed a considerable ability to predict muscle activation accurately.

Muscle Type	Precision	Recall	F1-Score	Accuracy
LD	0.9030	0.8232	0.87304	0.9095
ST	0.9225	0.8917	0.9069	0.9273

Table 4: Performance metrics of the LSTM onset model for the LD and ST muscle types.

Figure 4 presents the LSTM model's performance in detecting the onset of ST muscle activation.

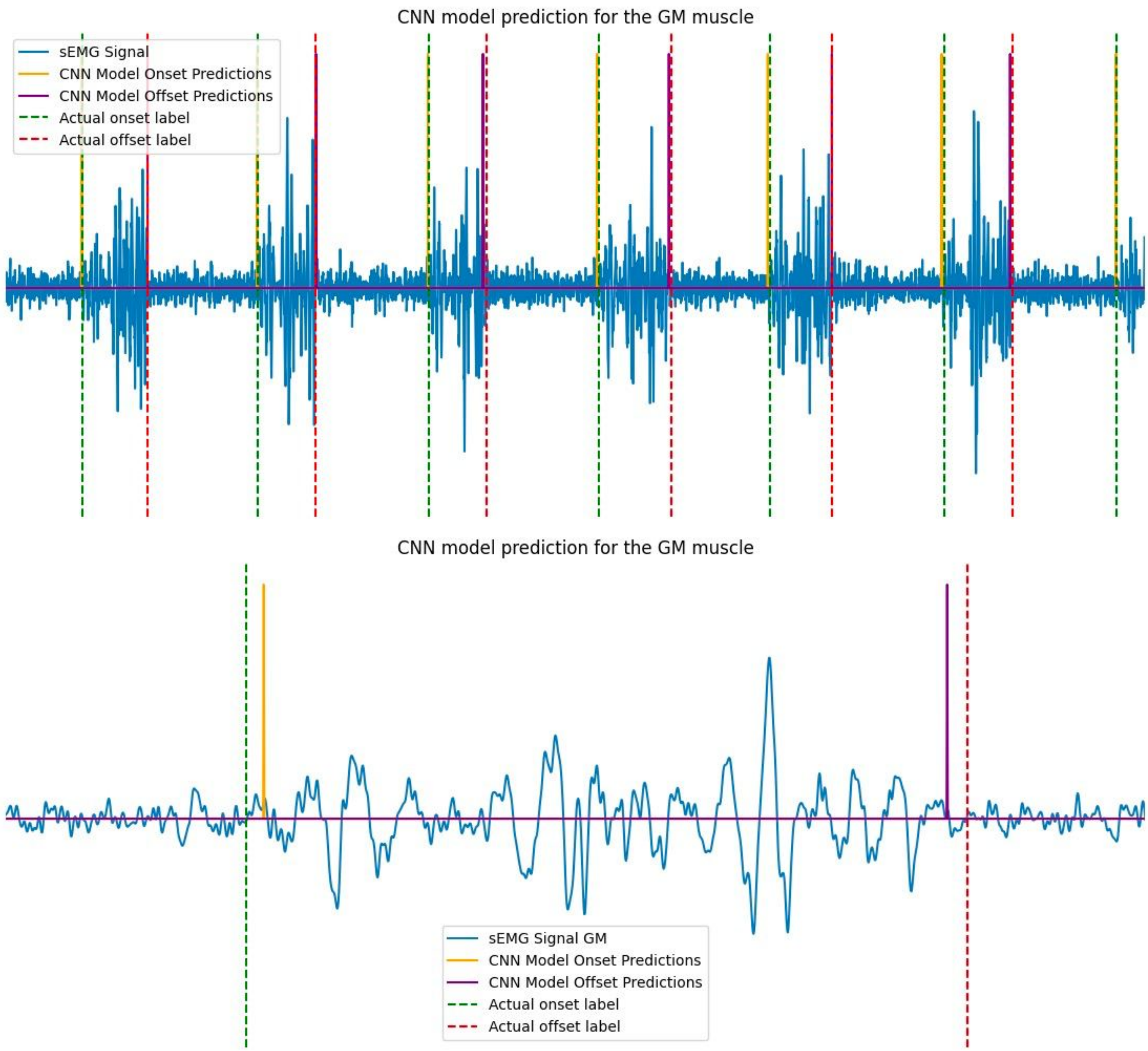

Figure 3: Performance of the CNN model in detecting the onset and offset of muscle activation for the GM muscle.

The LSTM model's performance, as revealed by the data, demonstrates its potential for accurate muscle activation onset detection. This underlines the LSTM model's suitability for further exploration in the field of equine gait analysis and rehabilitation.

5 DISCUSSION

Given that our data was collected at a frequency of 4000Hz, a window size of 500 data points corresponds to a time window of 0.125 seconds. Thus, the temporal accuracy of our models cannot exceed this 125ms threshold. This can be crucial for some applications and needs to be considered carefully, as many studies in human participants opted for higher accuracy.

We tested Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs) in our study as innovative tools for the detection of muscle activation onset and offset from equine sEMG data. Both models demonstrated robust performance across different muscle types.

The performance of the CNN model remained consistent across various muscles for the detection of muscle activation onset and offset. Nonetheless, a slight decrease in model performance was observed when data from multiple horses were combined, suggesting

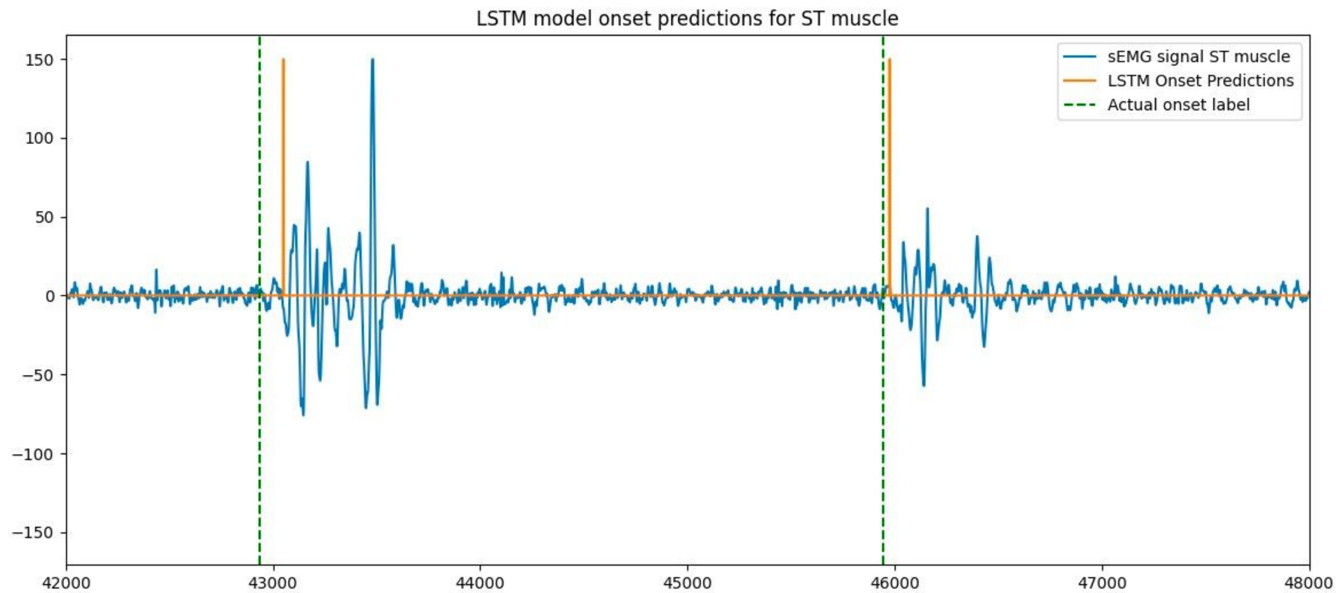

Figure 4: Performance of the LSTM model in detecting the onset of ST muscle activation.

that inter-individual differences among horses may subtly affect the model's performance. This highlights the potential need for individualized models or normalization techniques [10].

Despite its complexity and lengthy training times, the LSTM model showed notable performance for the Semitendinosus (ST) muscle [9]. However, these factors might constrain its utility in real-time applications or when computational resources are limited. We also tried a simpler version of the LSTM model, however, the results were considerably worse. This underscores that despite offering high precision, the LSTM model may not always be the optimal choice due to its computational requirements and complexity.

6 CONCLUSION AND FUTURE WORK

For the analysis of equine sEMG data, we demonstrated the potential benefits of machine learning techniques, specifically Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs). These techniques successfully identified the onset and offset of muscle activation across multiple muscle types, demonstrating how useful they might be in veterinary science and, specifically, in the context of equine sEMG data interpretation.

Our findings contribute to the growing field of machine learning applications in veterinary science and contribute to a greater understanding of the muscle function of horses. This information contributes to the development of more efficient training and rehabilitation programs. When data from multiple horses were combined, however, the efficacy of the models decreased, highlighting the need for individualized models or normalization procedures that account for variability between horses. Future research should evaluate the generalizability of these models by analyzing their efficacy across a variety of exercise routines and conditions. The applicability of these models in other aspects of sEMG data interpretation, such as the detection of muscle fatigue and the classification of various muscle activities, should also be evaluated in future research.

Despite the encouraging results of this study, it is crucial to validate these advanced machine learning methodologies with more classical threshold methods, such as those using Root Mean Square (RMS) calculations. Such comparative studies could provide deeper insights into the strengths and limitations of each approach, potentially guiding the development of hybrid models.

An additional area for future research lies in the refinement of the methods used to process the output from these models. While our approach of filtering the raw predictions to identify a single onset and offset point within a specified time frame was effective for this study, further investigation may yield more optimal methods for this processing stage.

In summary, our study underscores the potential of machine learning, specifically CNNs and LSTMs, in the analysis of equine sEMG data. We have laid the groundwork for future research in this field, highlighting the need for continued exploration and refinement of these techniques to advance our understanding of equine muscle function.

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