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DEEP LEARNING ALGORITHM FOR IMAGE CLASSIFICATION OF WAVEFORMS OBTAINED FROM ELECTRICALLY STIMULATED HYPOXIC SKELETAL MUSCLE BUNDLES

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ABSTRACT

Acute compartment syndrome is a serious condition that requires urgent surgical treatment. While the current emergency treatment is straightforward - relieve intra-compartmental pressure via fasciotomy - the diagnosis is often a difficult one. A deep neural network is presented here that has been trained to detect whether isolated muscle bundles were exposed to hypoxic conditions and became ischemic.

Keywords: compartment syndrome, deep learning, ischemia

INTRODUCTION

Acute compartment syndrome (ACS) is an orthopedic emergency that typically requires surgical intervention in order to alleviate an elevated intra-compartmental pressure (ICP) within the osteofascial compartment. It is generally accepted that the principal mechanism of ACS is impaired capillary perfusion caused by the increased ICP [1]. Prompt decompression is necessary to avoid irreversible ischemic damage to both muscle and nervous tissue and secondary complications from the myonecrosis, such as rhabdomyolysis. However, ACS is difficult to discern.

Currently, an ACS diagnosis relies on a physical examination with invasive ICP measurements as required supporting evidence. For example, the Stryker ICP Monitor System is commonly used for such ICP measurements [1], but controversy exists regarding the use of ICP as a primary indicator of ACS and also the accepted ICP threshold value has been contested [2].

We consider here, that machine learning approaches can be leveraged to aid in the rapid detection of ACS. Here we utilized a deep learning algorithm that was able to detect hypoxic skeletal muscle, based on their electrically stimulated force profiles.

METHODS

Fresh diaphragm tissue specimens were obtained from swine (n=24). From each specimen multiple muscle bundles were dissected and mounted in isolated tissue baths (Figure 1) containing a Krebs-Ringer solution bubbled with carbogen (95% O_2, 5% CO_2) and maintained at 37°C. Ends of muscle bundles were attached to both a force transducer and a stationary hook. The muscle bundles were then allowed to recover from the dissection while being subjected to field stimulation with a 1 ms square-wave pulse at a 0.1 Hz frequency. Upon stabilization, the stimulation voltage was set to a supramaximal level and length-tension relationship was optimized, such that maximal isometric twitch force was achieved. These parameters were maintained for the duration of the experiment.

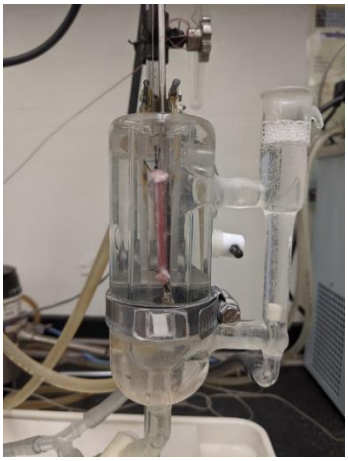

Figure 1. Isolated tissue bath containing a diaphragm muscle bundle attached to both force transducer and stationary hook and flanked by platinum stimulating electrodes.

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Muscle bundles were grouped into either hypoxic treatment (n=63) or controls (n=56). Control muscle bundles remained on carbogen while hypoxic muscle bundles were made so by being gassed with 95% N_2, 5% CO_2. The treatment period lasted for one hour. Data acquisition was performed using a custom-built software; force data was sampled at 100 Hz.

The force profiles of twitch responses were plotted for each muscle bundle at the 30 minute, 45 minute, and 60 minute time points. Images were created by shading in the area under the curve for each of these plots. A representative image is shown in Figure 2.

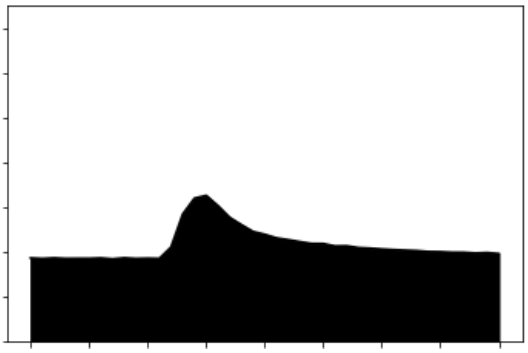

Figure 2. Representative image of a hypoxic muscle bundle twitch force profile after 45 minutes of hypoxia.

A total of 357 images were computationally generated. The dataset was split by muscle bundle between training and validation sets to prevent data leakage. 80% of muscle bundles and their image subsets (285 images) were assigned to the training set. The other 20% of muscle bundles and their image subsets (72 images) were reserved for validation of the model. Image transformations were performed on these datasets, however the images were not flipped in order to maintain temporal information of the twitch waveform.

A ResNet34 architecture pre-trained on the ImageNet dataset [3] was trained using one cycle learning rate policy [4]. The batch size was set at 64. Four frozen layers were trained at a learning rate of 3E-3. Twenty unfrozen layers were then trained at learning rates incremented between 1E-5 and 1E-3.

RESULTS

The neural network was able to achieve an accuracy of 91.7% in the classification of the twitch waveform images in the validation set. The results are illustrated in Figure 3. 3 of 36 control images were misclassified as hypoxic, while 3 of the 36 hypoxic images were misclassified as normoxic.

While the results show that the neural network is capable of predicting whether a muscle bundle is hypoxic, specificity was not addressed.

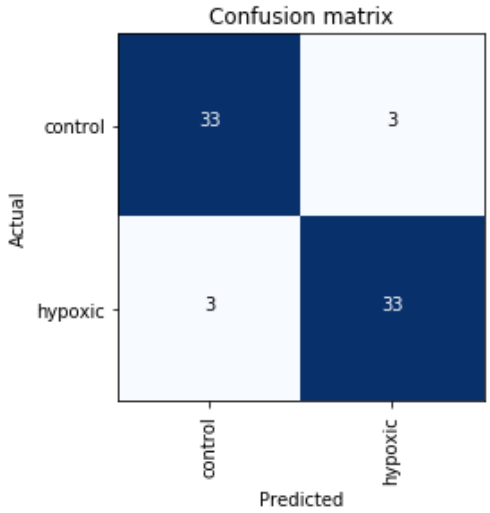

Figure 3. Shown here is a confusion matrix illustrating the incidence of correct and incorrect classifications.

CONCLUSION

This work indicates that it may be possible to accurately predict whether a muscle bundle is experiencing hypoxic conditions from twitch force waveform data, using a neural identification network. Transfer learning with a ResNet34 was used here due to ease of implementation and good performance. Alternative classifiers and convolutional neural networks will be investigated in the future.

While this initial approach shows sensitivity, specificity was not addressed. Future work should attempt to distinguish from different treatment/damaging conditions. Additionally, we are working to incorporate other markers of muscle ischemia, as means to further investigate whether compartment syndrome could be predicted using a data driven approach.

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