Using Wearables to Predict Biceps Fatigue: A Preliminary Perspective

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ABSTRACT

In 2015, there were 376,190 cases (33% of all injury cases) of musculoskeletal disorders caused by biceps overuse and overexertion lifting in the United States alone. In fact, these injuries are not only common in workplaces but also costly, in the USA alone is estimated to approximately $190 billion and have resulted in over 1.1 million lost days of work. One contributing factor to such injuries is excessive fatigue, which can result in muscle strain that requires 1 up to 22 weeks of treatment or tendons rupture that results in a permanent substantial decrease in biceps strength. Thus being able to detect biceps fatigue during an activity when excessive fatigue sets in, could be of great practical importance. In this paper, we explore whether we can predict fatigue by using machine learning to estimate the rating of perceived exertion (RPE) from inertial sensor data of individuals. We collected a longitudinal dataset of biceps concentration curls, and demonstrate that machine learning can be used to build accurate models for predicting fatigue. We were able to achieve an average fatigue prediction accuracies of 81% and 94% for all-status and fatigue-only, respectively, by using a 1-layer (7) FNN. Also, we were able to build cross-person fatigue detection model with an accuracies of 71% and 87% for all-status and fatigue-only, respectively, by using a 2-layers (7,5) FNN.

CCS CONCEPTS

• **Information systems** → **Data mining**; • **Applied computing** → *Health care information systems*;

KEYWORDS

Neural Networks, Sports Analytics, Wearables

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1 INTRODUCTION

Biceps is a muscle in the anterior compartment of the upper arm, along with the brachialis muscle and the coracobrachialis muscle [4]. The biceps are usually attributed as representative of strength within a variety of worldwide cultures [15]. Part of the popularity of biceps is their functionality and collaboratively [23, 26]. biceps are one of the most active functional skeletal muscle which flexes the arm at the elbow joint countless times each day for picking, lifting, and pulling objects. Also, bicep collaborate between brachialis and brachioradialis for flexion at the elbow joint, as well as, utilize shoulders and back muscles as stabilizers.

While biceps have several benefits, injuries hamper these benefits and can even be detrimental for the injured. A classifications of muscle injuries in sport were carried by previous studies [15, 18] indicate that muscle fatigue has been commonly shown to predispose to injury. In fact, these repetitive motions of biceps during muscle fatigue can lead to lower-back and upper-limb injuries that reduce productivity [25]. According to US Department of Labor in 2015, there were 376,190 cases (33% of all injury cases) of musculoskeletal disorders caused by biceps fatigue and overexertion in lifting [17]. In fact, the cost of these injuries in the USA alone is estimated to approximately $190 billion and have resulted in over 1.1 million lost days of work [12]. Biceps perform limited repetitive movements due to its placement in the anterior compartment of the upper arm. This repeatedly stresses the same muscle structures (e.g., muscle tissues, tendons or joints) over time, and will eventually introduces biceps fatigue which if it exceeds the structure's stress tolerance, it will result in overuse injuries [16]. Typical overuse biceps injuries include muscle strain which can require 1 up to 22 weeks of treatment [9, 14] or tendons rupture which results in a permanent substantial decrease in flexion and supination strength [16].

In this work, we utilize Feedforward neural network (FNN) and Neblina IMU device to predict fatigue during an activity for example, a concentration curls exercise. Generally, gym exercises contain repetitive actions which form patterns; thus, sensors readings have a periodicity nature. Also, prolonged gym activities generate fatigue which diverges the exercises patterns; thus, distorting the sensors readings. This negatively impacts fatigue systems by misleading them to false detects; thus, hindering their accuracy. This work has two contributions as the following:

(1) This work provides an approach to a fatigue perception model which detect fatigue during a gym exercises. Such a model can reduce misleading results induced by fatigue; thus, improving HAR systems activity. As a result, it can protect athletes from fatigue induced injuries such as muscle strain which can require 1 up to 22 weeks of treatment.

(2) This work collected, segmented and labelled a fatigue dataset for concentration curl exercise.

Paper Organization. Section 2 provides definitions of fatigue, how to measure it, and challenges posed by this task. Section 3 illustrates our approach to fatigue prediction, data processing, feature extraction, and building a learning model. Section 4 explains the validation of our approach and presents our findings. Section 5 concludes our paper.

2 FATIGUE: DEFINITION, DATA COLLECTION, AND CHALLENGES

In this section, we look into the definition of fatigue and how to measure it, then we describe our dataset, and we finish with a discussion of the challenges posed by this task.

2.1 Defining Fatigue

The term muscle fatigue is used to denote a transient decrease in the capacity to perform physical actions [8]. There have been few principles have emerged to characterize the range of effects ascribed to muscle fatigue. According to the following definitions, we observe that fatigue can be defined as the decline in the performance or the exerted force over time:

- 'Intensive activity of muscles causes a decline in performance, known as fatigue...'[1].
- 'Performing a motor task for long periods of time induces motor fatigue, which is generally defined as a decline in a person's ability to exert force...'[13].
- 'The development of muscle fatigue is typically quantified as a decline in the maximal force or power capacity of muscle...'[8].
- '...a more focused definition of muscle fatigue as an exercise-induced reduction in the ability of a muscle to produce force or power whether or not the task can be sustained...'[2].

Based on the aforementioned definitions, biceps fatigue implies a decrease in biceps performance (i.e., decreased average exerted force) due to a prolonged task involving repitative movements from biceps. Eventually, biceps will reach its physiological limitations (i.e., lactate threshold) that bring about biomechanical compensations (i.e., alterations in the forces and kinematics). Although there are several approaches to capture a biceps fatigue [19, 20, 22], yet not all of them are practical for our task. Hence, we developed four criteria for defining a practical approach to capture biceps fatigue:

- **Non-invasive:** it does not introduce any instruments into the body. In other words, it does not require a puncture in the skin or contact with the mucosa. Whereas the invasive approaches always require blood lactate [24], creatine kinase [11], or rectal temperature [7].
- **Convenient:** it does not hinder the person's comfort in any way and does not interfere with the person's movement. Whereas other approaches may include metabolic systems that require a face mask which is inconvenient in public and often hinder a person's comfort. These approaches usually measure gas exchange (i.e., volume of oxygen consumed (VO_2))[3].
- **User-friendly:** practically, it does not require more than the user him/herself to use the data acquisition device "wearables" and it should not interrupt the person's activity or require mental effort to capture the data. Whereas, other approaches such as Hooper's Index [10] or the profile of mood states (POMS) [27] require cognitive loads that force measurements to be attained prior or post activity.
- **Peripheral muscle fatigue:** muscle fatigue can occur in two basic mechanisms: (a) central involves proximal motor neurons (mainly in the brain); and (b) peripheral involves within the motor units (i.e., motor neurons, peripheral nerves, motor endplates, muscle fibers). Although other approaches such as heart rate (HR) [21] may fulfill the criteria of being non-invasive, convenient, and user-friendly, it measure fatigue based on the cardiovascular only, rather than the musculoskeletal response at an activity which has closer links to overuse injuries.

In this work, we measure biceps fatigue using the rating of perceived exertion (RPE) which is a subjective measure of fatigue that is widely used within sport science where table 1 can be viewed as partial truth label. Basically, we use the Borg scale [6] to matches how hard a person feel with numbers from 6 to 20, as shown in table 1. The scale starts with "no feeling of exertion", which rates a 6, and ends with "very, very hard", which rates a 20. Moderate activities register 11 to 14 on the Borg scale ("fairly light" to "somewhat hard"), while vigorous activities usually rate a 15 or higher ("hard" to "very, very hard"). Borg rating is set to run from 6 to 20 as a simple way to estimate heart rate-multiplying the Borg rating by 10 gives an approximate heart rate for a particular level of activity. RPE is non-invasive, convenient, and user-friendly due to its measurement simplicity. Moreover, RPE measures peripheral muscle fatigue, given that it provides a more comprehensive view which includes feedback from cardiovascular, respiratory and musculoskeletal systems [7]; hence, it meets our four criteria. Furthermore, RPE has been shown to model a person's performance better in the real-world compared to heart rate which is less responsive to different terrain types [5]; thus, RPE is an appropriate and validated marker of a person's fatigue [6].

2.2 Collecting Data

In order to collect data for this work, ten males participants with ages between 29-33 preformed concentration curls with a 4.5 kg dumbbell. Figure 3 visually illustrates the data acquisition sessions, we asked each participant to perform 5 sets/hand and 15 repetitions/set. In total, we collected a longitudinal data for 1,500 concentration curl repetitions. Prior to the start, we explained the RPE scale. Then each participant did 5 repetitions to warm-up followed by the 15 repetitions/set. The participants reported their RPE after each set, including the warm up, yielding six RPE values/hand.

During the recoding sessions, one 50Hz inertial measurement unit (IMU) (Neblina) was placed on participant's wrist. This wearable IMU contains a 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer that measures one signal for each of the three orthogonal axes per sensor type, resulting in nine signals per IMU. Each participant followed instructions to assured the exercise correctness as the following:

Table 1: Borg G.A. Psychophysical bases of perceived exertion [6]

Perceived exertion	Borg rating	Examples
None	6	Reading a book, watching television
Very, very light	7 to 8	Tying shoes
Very light	9 to 10	Chores like folding clothes that seem to take little effort
Fairly light	11 to 12	Walking through the grocery store (effort but without speeding up your breathing)
Somewhat hard	13 to 14	Brisk walking (moderate effort and speeding up your breathing but don't make you out of breath)
Hard	15 to 16	Bicycling, swimming, (vigorous effort and get the heart pounding and make breathing very fast)
Very hard	17 to 18	The highest level of activity you can sustain
Very, very hard	19 to 20	A finishing kick in a race or other burst of activity that you can't maintain for long

Figure 1: The starting position in concentration curl

Figure 2: The contracting position in concentration curl

(1) Sit down on a flat bench with one dumbbell in front of you between your legs. Your legs should be spread with your knees bent and feet on the floor.
(2) Use your right arm to pick the dumbbell up. Place the back of your right upper arm on the top of your inner right thigh. Rotate the palm of your hand until it is facing forward away from your thigh. Your arm should be extended and the dumbbell should be above the floor. This will be your starting position, as shown in Figure 1.
(3) While holding the upper arm stationary, curl the weights forward while contracting the biceps as you breathe out. Only the forearms should move. Continue the movement until your biceps are fully contracted and the dumbbells are at shoulder level. At the top of the movement make sure that the little finger of your arm is higher than your thumb. This guarantees a good contraction. Hold the contracted position for a second as you squeeze the biceps, as shown in Figure 2.
(4) Slowly begin to bring the dumbbells back to starting position as your breathe in. Avoid swinging motions at any time.
(5) Repeat for 15 repetitions. Then repeat the movement with the left arm.

2.3 Challenges

Using a subjective measure of fatigue such as RPE introduces a dependency between the correctness of selected Borg rating and participants awareness:

- **C1: The subjectivity of RPE,** participants may rate their exertion level differently based on their personal evaluation for feeling fatigued. Moreover, it is often hard for participants to accurately assess their exertion level gradually throughout the test.

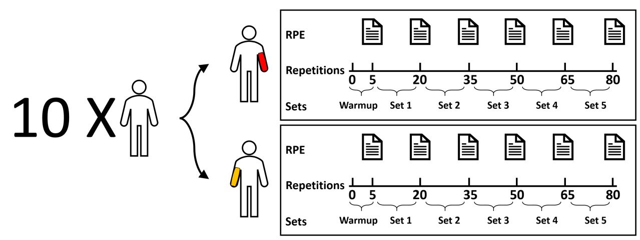

Figure 3: Visualization of the data acquisition sessions

- **C2: Familiarity with RPE,** in the beginning, participants were unfamiliar with the RPE prior to the data acquisition sessions; perhaps, they were unsure how to use it at first. The longitudinal nature of the data acquisition sessions helped participants to become more familiar with the scale as they performed more sets, and therefore their use of the RPE potentially evolved across consecutive sets.

In order to mimic the normal biceps movements (e.g., self-select lifting speed) during an activity , introduces a number of challenges into the data that should be accounted for:

- **C3: Variable lifting speed,** lifting speed, and changes in it, impact the measured inertial motion data (e.g., higher speed means higher acceleration measurements). As we are only interested in fatigue-induced changes in the data we need methods that are robust to speed changes.
- **C4: Individual status,** we consider the fact that, a participant can be in one of the following status. 1)Active status, the participant is performing an activity normally, without feeling fatigued. 2) Idle status, the participant is taking a rest between activities. 3) Fatigue status, the participant is

performing an activity while feeling fatigued where the risk of overuse injuries rises.

3 FATIGUE PREDICTION APPROACH

In this section, we outline our approach to fatigue prediction. First, we discuss the data processing and feature extraction. Second, we describe how to address the challenges described in Subsection 2.3. Third, we discuss how to build a learning model.

3.1 data processing and feature extraction

The collected data contained accelerometer, gyroscope, and magnetometer signals where each signal represented one of the three orthogonal axes per sensor type. These signals were converted to the three-dimensional Cartesian coordinates (x, y, z) for better representations. Later, we omitted the magnetometer data as this signal, in isolation, does not provide information about fatigue. Also, we augmented the data by deriving two additional signals from the accelerometer data from an IMU:

- **Total Acceleration:** this signal is less dependent on the exact attachment of the accelerometer as it combines the x, y, and z acceleration signals at time t_i , and is defined as: $\sqrt{a_{x_i}^2 + a_{y_i}^2 + a_{z_i}^2}$.
- **Exerted Force:** force is the "push" or "pull" exerted on an object to make it move or accelerate. Newton's second law of motion describes how force is related to mass and acceleration, and this relationship is used to calculate force, as following: $F_{net} = F_{exerted} - F_{grav}$ where $F_{exerted} = m \times a$ is the exerted force by the participant to lift an object. $F_{exerted}$ is calculated by multiplying the mass m of the lifted object by acceleration a. On the other hand, $F_{grav} = m \times g$ is the force of gravity on earth which always equals to the weight of the object. F_{grav} is calculated by multiplying the mass m of the lifted object by gravitational acceleration g

In total, IMU provides 3-axis gyroscope and 3-axis accelerometer signals, in addition, we compute two more signals which are total acceleration and exerted force. Then, we generate 24 features by computing the mean, standard deviation and mean absolute deviation for all signals. In summary, we were able to record 8 time series signals with one IMUs and extract 24 features from them. However, we still need to evaluate these feature to answer RQ1 in section 4.

3.2 Addressing the challenges

To deal with the challenges C1 and C2 related to the subjective nature of the RPE outlined in Subsection 2.3, we apply min-max normalization to the RPE value based on the current set. This normalization helps to account for subjective differences in RPE. First, each participant may interpret the scale differently and report a different range of values. Second, the first RPE value reported in a set may serve as an anchor for subsequent ratings in that set. The minimum value is the RPE reported after the warm up and the maximum value is 20, which is the highest RPE value on the Borg scale. We used this value because using the final RPE value from the set would cause the current label to depend on future data, which is not methodologically sound. To help mitigate the effect of challenge C3 mentioned in Subsection 2.3. we standardized all signal within an set. For each signal in an set, we subtract the repetition's mean value for that signal and divide it by the signal's standard deviation in that set. On average, each set consisted of 15 repetitions is completed approximately in 60 seconds and described by 8 time series signals in section 3.1. So, With a 0.5 second windows and a sampling rate of 50Hz, a set is reduced from 3K data points to 120 for each time series signals described in section 3.1. In section 4 (RQ2), we address challenge C4 where we define idle status represents Borg score from 6 to 10, active status represents Borg score from 11 to 16, and fatigue status represents Borg score from 17 to 20.

3.3 Learning model

We consider two different learning models using FNN, each learned based on different subsets of the data:

- **Individual Model**: it is one personalized model for each participant and it uses only data of that participant. This model would work well if each subject has a unique pattern in response to fatigue accumulation.
- **General Model**: this is a single model for all participants. It uses data from all participants to leverage all the data with the assumption that multiple subjects will have similar changes in style as a response to fatigue.

4 EXPERIMENTAL EVALUATION

The goal of the empirical evaluation is to assess the reliability of predicting fatigue during concentration curls exercise and discuss the practical impact of the results. Specifically, we address the following questions:

- RQ1: What are the important features to predict biceps fatigue?
- RQ2: How accurate can we predict biceps fatigue?
- RQ3: What is the impact of generalized or personalized models?

In the following subsections, we will detail the motivation, approach, and the findings for each research question.

4.1 RQ1: What are the important features to predict biceps fatigue?

Motivation: The reasons behind finding the important features to predict fatigue is to reduce FNN complexity, as well as, the noise induced by insignificant features which may hinder FNN performance. This could have a positive impact in terms of power consumption and computational expenses.

Approach: To address this research question, we have to look into the data which is Neblina IMU that contains 3-axis gyroscope, accelerometer, and magnetometer, in addition to, total acceleration and exerted force. we use spearman's rank to shows how correlated are the mean, standard deviation and mean absolute deviation for all signals with person's activity status. Also, we eliminated all elements with significance level less than 0.5. Figure 4 presents the correlation matrix for mean absolute deviation of the collected data. The figure shows that person's activity "fatigue" is positively correlated with the mean absolute deviation of the 8 elements with variant degrees of strength which are the mean absolute deviation

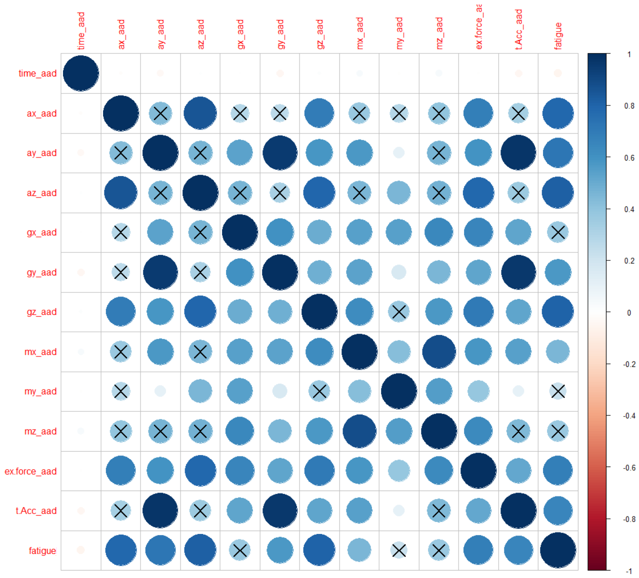

Figure 4: Graphical display of a correlation matrix for mean absolute deviation features.

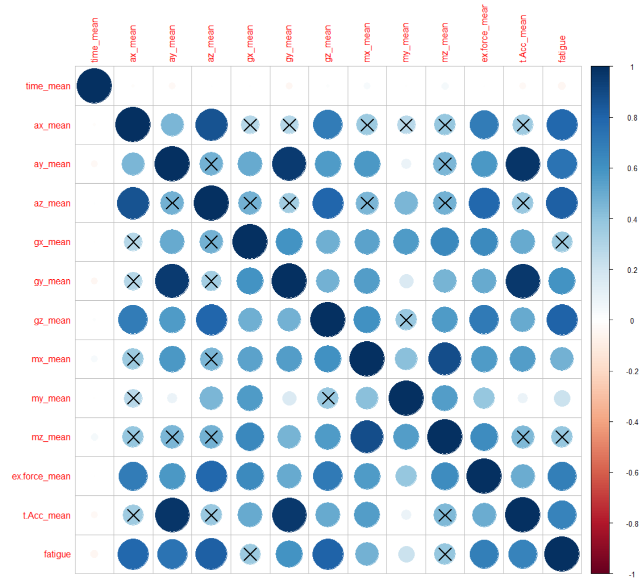

Figure 5: Graphical display of a correlation matrix for mean features.

of (x,y,z)-axis from accelerometer, (y,z)-axis from gyroscope, x-axis from magnetometer, exerted force, and total acceleration. Figure 5 presents the correlation matrix for mean of the collected data. The figure shows that person's activity "fatigue" is positively correlated with mean of (x,y,z)-axis from accelerometer, (y,z)-axis from gyroscope, (x,y)-axis from magnetometer, exerted force, and total acceleration. Figure 6 presents the correlation matrix for standard deviation of the collected data. The figure shows that person's activity "fatigue" is positively with standard deviation of (x,y,z)-axis from accelerometer, (y,z)-axis from gyroscope, (x,y)-axis from magnetometer, exerted force, and total acceleration. From figures 4 and 5 we concluded that both mean and standard deviation features have similar correlation and significance levels. Therefore, we selected only the mean features to help reducing the FNN complexity. In the end, we selected 14 features as the following: the mean and the mean absolute deviation of the collected data from (x,y,z)-axis from accelerometer, (y,z)-axis from gyroscope, exerted force, and total acceleration.

We used all of the 14 features as inputs to a simple FNN consists of 1-hidden layer (7) and 2-hidden layer (7,5) to build individual and general fatigue models, respectively.

4.2 RQ2: How accurate can we predict biceps fatigue?

Motivation: The reasons behind measuring the accuracy of predicting fatigue in concentration curls are assessing the reliability for the work and its ability to differentiate the periods of time when fatigue exists. We define two type of accuracies, first, an all-status accuracy which is defined as the argument of the predicted status to the true status of the person. This means we consider all of the three statuses as outcomes in our prediction. As a result, we are able to measure how accurate our model can differentiate between all of the three statuses if needed. Second, a fatigue-only accuracy which is defined as the argument of whether the predicted status is a fatigue or not. This means we have a single binary status as an outcome in our prediction. As a result, we are able to measure how accurate our model can focus on predicting fatigue-only statuses if needed.

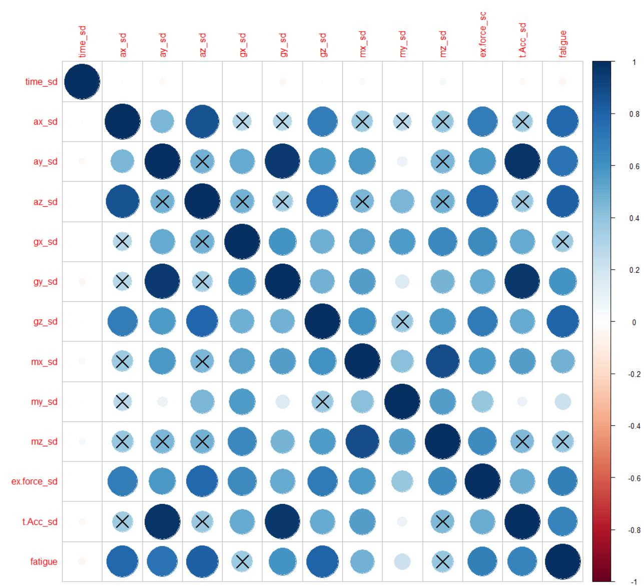

Figure 6: Graphical display of a correlation matrix for standard deviation features.

Table 2: All-status accuracy confusion matrix

		Actual		
		Active	**Idle**	**Fatigue**
Predicted	**Active**	True Active	False Active	False Active
	Idle	False Idle	True Idle	False Idle
	Fatigue	False Fatigue	False Fatigue	True Fatigue

Table 3: Fatigue-only confusion matrix

		Actual	
		Fatigue	**Non-Fatigue**
Predicted	**Fatigue**	True Fatigue	False Fatigue
	Non-Fatigue	False Non-Fatigue	True Non-Fatigue

Approach: To address this research question, we train/test FNN to predict the Borg rating for each set. We calculate the all-status accuracy using the confusion matrix shown in Table 2, where idle status represents Borg score from 6 to 10, active status represents Borg score from 11 to 16, and fatigue status represents Borg score from 17 to 20. where all-status accuracy

$$= \frac{True(Active + Idle + Fatigue)}{True(Active + Idle + Fatigue) + False(Active + Idle + Fatigue)}$$

On the other hand, we calculate the fatigue-only accuracy using the confusion matrix shown in Table 3, where fatigue-only accuracy

$$= \frac{True(Fatigue + Non - Fatigue)}{True(Fatigue + Non - Fatigue) + False(Fatigue + Non - Fatigue)}$$

Result: In Table 4, we use single hidden layer configurations of FNN. First FNN consists of one hidden layer with 3 neurons which achieves an average all-status and fatigue-only accuracies of 37% and 54%, respectively. Then, we expanded the first layer to 5 neurons, as result, the second FNN achieves a higher average all-status and fatigue-only accuracies of 70% and 72%, respectively. Lastly, we expanded the first layer to 7 neurons, as result, the third FNN achieves a higher all-status and fatigue-only accuracies to 81% and 94%, respectively.

Table 4: Average all-status and fatigue-only accuracies achieved using three configurations of FNN

FNN	Accuracy	
	All-status	**Fatigue-only**
(3)	37%	54%
(5)	70%	72%
(7)	81%	94%

> ***We were able to achieve an average fatigue prediction accuracies of 81% and 94% for all-status and fatigue-only, respectively, by using a 1-layer (7) FNN.***

4.3 RQ3: Can we build a cross-person fatigue detection model?

Motivation: The reasons behind building a cross-person fatigue detection model are assessing the generality of the extracted features and the ability to detect fatigue across different persons.
Approach: To address this research question, we use data from 9 participants as the training set then, we test the FNN on the 10^{th} participant data. As a result, we were able to train and test the 2-hidden layer FNN 10 times using each participant data as a testing set individually. Then, we calculate the all-status accuracy using the same equation and the confusion matrix presented in RQ2. Similarly, we calculate the fatigue-only accuracy using the same equation and the confusion matrix presented in RQ2.
Result: In Table 5, we use 2-hidden layers configurations of FNN. First FNN consists of 2-hidden layers with (7,1) neurons which achieves an average all-status and fatigue-only accuracies of 37% and 44%, respectively. Then, we expanded the second layer to 3 neurons, as result, the second FNN achieves a higher average all-status and fatigue-only accuracies of 50% and 61%, respectively. Lastly, we expanded the second layer to 5 neurons, as result, the third FNN achieves a higher all-status and fatigue-only accuracies to 71% and 87%, respectively.

Table 5: Average all-status and fatigue-only accuracies achieved using three configurations of 2-layers FNN

FNN	Accuracy	
	All-status	**Fatigue-only**
(7,1)	37%	44%
(7,3)	50%	61%
(7,5)	71%	87%

> ***We were able to build cross-person fatigue detection model with an accuracies of 71% and 87% for all-status and fatigue-only, respectively, by using a 2-layer (7,5) FNN.***

5 CONCLUSION

This paper introduced fatigue prediction in biceps concentration curls as a new significant, interesting, and impactful data science problem. Specifically, its significant challenges arise from analyzing sensor data collected and the need to to selecting suitable features and evolving truth label for fatigue. We were able to achieve an average fatigue prediction accuracies of 81% and 94% for all-status and fatigue-only, respectively, by using a 1-layer (7) FNN. Also, we were able to build cross-person fatigue detection model with an accuracies of 71% and 87% for all-status and fatigue-only, respectively, by using a 2-layer (7,5) FNN. Moreover, our methodology effectively accounts for lifting speed, the different possibilities of user's status; thus, the results presented in this work are useful and represent a solid start for moving into a real-world application for monitoring the fatigue level of biceps muscles using wearable sensors.

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