Detection of Bicep Form Using Myoware and Machine Learning

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Abstract Many people have been exercising at home since the beginning of the COVID-19 period. Due to this, they haven't had the supervision of a professional trainer who could correct them, rectify their mistakes, and prevent from harmful injuries. One very common workout that people frequently do is the bicep curl exercise, yet they fail to maintain the right posture without realizing it and end up straining their back muscles and pulling their shoulders too far forward. This is very dangerous as it could result in long-term back pain and tendonitis. Considering this issue, a methodology has been proposed for the people at home to continue their regular exercises without any professional gym trainer and gym environment. This research is oriented toward the correction of bicep form during the bicep curl exercises and preventing injuries. The acquisition fragment is designed with Myoware, an open-source electromyography sensor along with a three-axis accelerometer for capturing the essential segments required for the analysis. Naïve Bayes, logistic regression, K-nearest neighbor, decision tree, and random forest classification models have been used to perform the classification of the data acquired. The analysis of the novel dataset attained has been effective for determining the model with the best results to detect the bicep form. The random forest classifier has yielded the highest individual accuracy of 90.90%. Ultimately, an app prototype has been developed using the MIT app inventor platform. It has been integrated with a Bluetooth module and google firebase for showcasing and collecting data in real time from the sensory modules

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to the person working out and simultaneously storing them in the database for the deployment of this test set in the machine learning model. With this, the results of the accuracy and performance of a person are then acquired on the app for expressing the nature of their workout session.

Keywords Machine learning · Random forest classification · Myoware · Electromyography · Three-Axis accelerometer

1 Introduction

This research focusses on the correction of bicep form during the bicep curl exercise for preventing muscle deformities in the arms and prolonged back pain. The biceps muscle is located at the front of the upper arm. At the elbow, it has one tendon that attaches to the radius bone, and two tendons that attach to the bones of the scapula bone of the shoulder. Biceps tendon injuries can result in proximal tendon rupture at the shoulder, proximal biceps tendonitis at the shoulder, and distal tendon rupture at the elbow. Even though tendons are tough, if they are stretched abnormally, they can cause soreness and pain. This is caused by micro tears in tendon called as tendonitis. It can occur due to a sudden and serious load to the tendon [1]. The bicep tendon located at the elbow most often tears during wrong and heavy lifting of an object such as a dumbbell. People who aspire to grow large muscles quickly are in a dilemma that they could achieve the goal by just lifting heavy weights but often ignore the fact that formation matters much more as poor form places undue emphasis on the muscles which leads to strains and sprains. Good mechanisms reduce overcompensation and likelihood of an injury. Electromyography is a diagnostic procedure for neuromuscular disorders and is used for medical research which helps in measuring muscle activation via electric potential [2].

Surface electromyography is a noninvasive research method that allows to evaluate the total bioelectrical activity of muscles at rest and during motor action performance of varying coordination complexity by recording the bioelectrical activity with surface electrodes installed cutaneous over the motor point of the muscle followed by signal analysis on the electromyograph [3–5]. The triaxial accelerometers measure the vibration in three axes X, Y, and Z. A range of useful information can be extracted from accelerometer-based measurements since each crystal reacts to vibration in a different direction [6]. Numerous studies have validated the use of accelerometers for gym and performance monitoring which span a wide range of disciplines including physical activity, orientation, and movement, as well as improving performance in athletes [7–11].

2 Literature Review

Intelligent IoT-based healthcare systems have recently gained massive recognition due to their compactness and accurate results. This has led many young inventors to design applications using sensors like surface electromyography (SEMG), accelerometer, gyroscope, pedometers, Electrocardiogram (ECG), and Electroencephalogram (EEG) to predict different body movements and conclude on the given results. Örücü and Selek [12] developed a multichannel wireless wearable SEMG system for real-time training performance monitoring, where four electro-potential SEMG sensors were used to get the data of four muscles in the upper isotonic muscle groups. A traditional SEMG circuit was implemented rather than using a standard sensor. This makes it less reliable and external conditions can throw off the accurate results required. The machine learning (ML) model implemented in our research uses both sensors to give precise output results which are more reliable.

The Myoware sensor and accelerometer are standard sensors that have been proven and tested for accurate outputs. Fuentes del Toro et al. [13] have validated this by comparing the accuracy with a commercially available sensor. A methodology was proposed where the subjects performed isometric and dynamic exercises while the Myoware and commercial systems were placed on the rectus femoris for obtaining the EMG signals from the maximum voluntary contractions of the muscle. Three indicators were developed to observe and assess the signals. They indicated good results with spearman's coefficient averaging above 60%, an energy ratio of above 80%, and a linear correlation coefficient of almost 100%. The results attained from this indicator exhibited a mean of 87% proving an adequate correlation between the signals.

Ramanarayanan [14] has used different types of wet or dry electrodes to measure exercise regimen for long-term muscle fatigue. Only the muscle activity has been taken as a parameter to conclude the results.

Logistic regression is typically used to identify the boundary between classes, and it indicates that class probabilities depend on the distance from the boundary [15]. In Naïve Bayes, there is only one parent and several children in a directed acyclic graph. Based on the context of their parents, this network assumes strong independence among the child nodes [16]. A clustering problem can be solved with K-means, a relatively simple unsupervised learning algorithm. Using a priori defined clusters, the procedure follows a smooth approach to classify a given dataset [17]. The decision tree classifies instances by sorting them according to their feature values. The nodes represent features in an instance to be classified, and branches represent values that nodes may assume. In this model, observations are mapped to conclusions about the item's target value by using a decision tree as a predictive model [18]. Random forest classifier grows many classification trees, and a bootstrapped sample of the training data is used to train each tree. The algorithm determines a split only by searching over a random subset of variables at each node of a tree. For the classification of an input vector in random forest, the vector is initially submitted as an input to each of the trees in the forest. Consequently, the classification is determined by a majority vote [19].

Osisanwo et al. [20] have discussed several supervised ML classification methods, where different attributes were compared and explained to evaluate the performance of each method. The following ML algorithms were evaluated: decision tree, random forest, Naïve Bayes, and support vector machines (SVM). For implementing the algorithms, a diabetes dataset was used and SVM was found to be the most effective in terms of accuracy and precision. The paper shows, however, that the performance of ML classification algorithms differs depending on the application problem and dataset in hand.

3 Methodology

The methodology proposed in this paper analyzes real-time results obtained from the sensors and concludes the results instantaneously with the ML model which helps in detecting faults earlier and can prevent long-term effects due to wrong form and posture.

The Myoware sensor attains the surface EMG signals which was placed on the biceps, while the position and orientation of the arm were determined by the accelerometer, located on the side of the shoulder at a 90° angle. The signals obtained from these two sensors simultaneously assisted in gathering the data between a healthy normal exercise and an abnormal injury causing exercise for generating a dataset. An analysis was carried out on the acquired signals while feature extraction and data preprocessing were implemented. Subsequently, ML approaches were applied for recognizing and classifying the form of the muscle during the exercise.

The proposed methodology for the correction of bicep form was branched into four phases, i.e., data acquisition, feature extraction and data preprocessing, ML model classification and monitoring the exercise via mobile application. Figure 1 illustrates the block diagram representation of the proposed model.

3.1 Data Acquisition

In the primary phase of the proposed methodology, EMG data of the bicep brachii muscle was acquired via Myoware muscle sensor along with the sensory data of an accelerometer to train the bicep curl exercise. EMG signals help in monitoring the voluntary contractions of the muscles. Myoware generates signals when it experiences contractions in the muscle. As the contraction in the muscle increases, the signal provides greater readings. For setting the sensor to provide reliable output and decrease any instantaneous fluctuations in the readings, sensitivity of the sensor was decreased by increasing the resistance offered by the potentiometer. Now, due

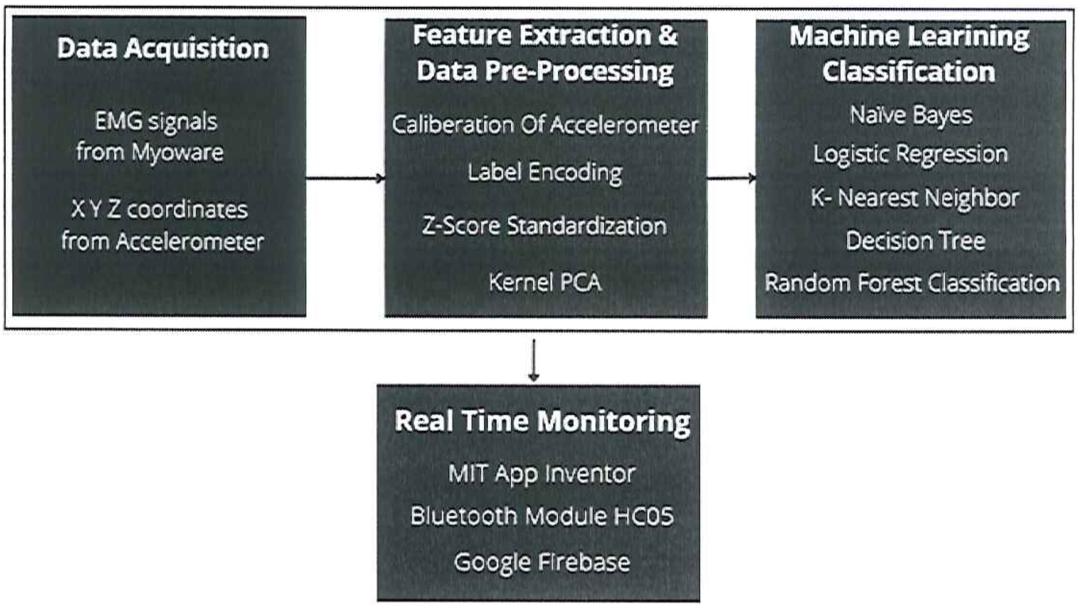


Fig. 1 Proposed model

to high resistance, the EMG signals would not fluctuate rapidly between the voluntary contractions and relaxations of the muscle and large signals could be shown as average signals.

The Myoware sensor was positioned on the bicep, while the reference electrode cable was placed at the triceps. The accelerometer was kept at a 90° angle at the corner of the shoulder on the deltoid muscle for monitoring the movement with respect to the bicep muscle and to provide the orientation and acceleration forces that were being utilized for measuring the direction and position of the arm at which the acceleration occurred.

3.2 Feature Extraction and Data Preprocessing

The values of X, Y, and Z coordinates obtained from the accelerometer via the microcontroller depend upon the sensitivity which can vary between $\pm$ 2 and $\pm$ 16 g [21]. Since the default sensitivity is $\pm$ 2 g, the corresponding output is often divided by 256 to get the values from $-$ 1 to $+$ 1 g. The 256 LSB/g means that we have 256 counts/g or per unit. However, in this proposed methodology, sensing higher acceleration forces was required and as a result, $\pm$ 16 g was selected as the sensitivity with the help of the data format register and its D_1 and D_0 bits [14]. Hence, for obtaining a range of $\pm$ 16 g the raw values had to be divided by 32.

In the dataset established, multiple labeled data was encountered during classification which could not be applied directly in the raw format. As a result, the data was labeled using label encoding, an efficient technique for converting labels into numeric forms that can be ingested into ML models. Table 1 shows the encoded

Table 1 Encoded values of the independent variables

Label name	Encoded value
Bicep_Correct_Form	0
Bicep_Wrong_Form	1

values of the two classes. It is a salient step in data preprocessing since it is a form of supervised learning and helps normalize labels such that they contain values between 0 and the total number of classes [22].

The training and the test set were split into an 80:20 ratio. The values for an attribute were standardized using the Z-score standardization which is based on the mean and standard deviation. The standardization ameliorates the convergence rate during the optimization process and helps in preventing the features with large variances from exerting an overly large impact during the model training [23]. As a result, the data acquired from Myoware, and accelerometer was standardized for removing the mean and scaling the independent variables to unit variance. The Z-score standardization formula is defined as:

Standardization:

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

Mean:

$$\mu = \frac{1}{N}\sum_{i=1}^{N}(x_i) \tag{2}$$

Standard Deviation:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{3}$$

where, x is the raw score, μ is the mean, and σ is the standard deviation.

Kernel principal component analysis (KPCA) is a nonlinear generalization of the famous linear data analysis method. Using integral operators and nonlinear kernel functions, it can systematically compute principal components in high-dimensional feature spaces. It illustrates the idea of mapping the input space into a feature space through nonlinear mapping for the computation of principal components in that feature map [24]. In this research, KPCA feature extraction was applied for identifying patterns in the data and detecting the correlation between the variables. Gaussian radial basis function was used as the kernel and the final number of extracted features was set to two components with which the visualization of the training and the test set resulted in a two-dimensional space. An impactful nonlinear relationship in the data was effectively captured by the proposed approach, and the classification performed significantly well.

3.3 Machine Learning Model Classification

After the preprocessing of data and intricate extraction of features, the model was trained on the dataset with the support of classification models. In this study, Naïve Bayes, logistic regression, K-nearest neighbor, decision tree, and random forest classification were used for performing the classification of each raw data sample. With the help of these classification models, the top model with best results was selected for the detection of the bicep form.

3.4 Monitoring the Exercise through MIT App Inventor

The MIT app inventor is a user-end application which was used for developing an app and integrating it with the Myoware and accelerometer via HC-05 Bluetooth module through which the data recorded by the sensors was displayed to the person working out in real time [25]. The data was simultaneously collected in Google Firebase which was utilized for generating a test set to deploy it in the ML model. Subsequently, at the end of each session the person was exhibited about their performance and accuracy for the bicep curl exercise.

3.5 Experimental Setup

In the proposed system of the design, the data was attained from two major sensors, i.e., the Myoware muscle sensor and the three-axis accelerometer. The communication between the accelerometer and Arduino nano was done through the I2C protocol. The serial clock pin and the serial data pin were interfaced with microcontroller's analog pins by which the Arduino pulsed at regular interval and the data was sent between the devices. The Myoware was bridged with the microcontroller by initially connecting its power supplies to the 5 V and GND, respectively, after which the output signal SIG was provided to an analog pin of the Arduino nano [2]. Also, the Bluetooth module HC-05 was setup for interaction with MIT app inventor. Figure 2 illustrates the circuit diagram for the proposed methodology.

The muscle sensor was placed on the bicep muscle. The adjustable gain end muscle electrode snap was positioned in the center of the muscle body and the mid muscle electrode snap was lined up downward in the direction of the bicep muscle length, while the reference electrode was positioned on the triceps muscle as shown in Fig. 3.

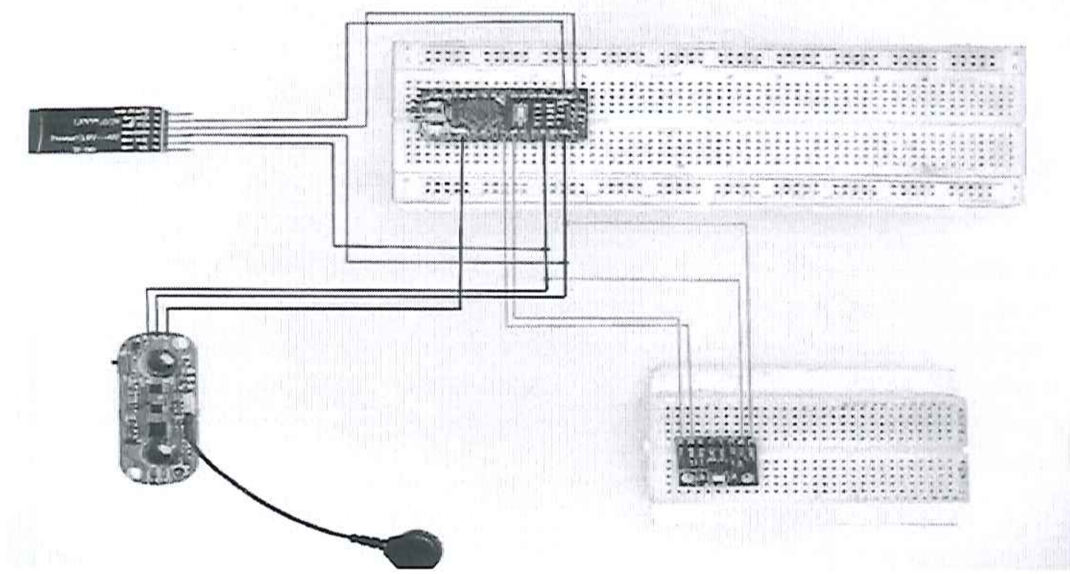
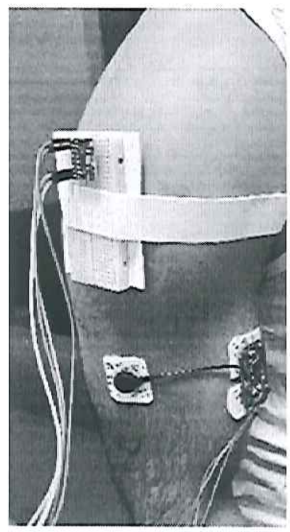


Fig. 2 Circuit diagram for the proposed design

Fig. 3 Complete setup of the proposed design



Each of the subjects performed two sets of the exercise. Each set included 20 counts in which the exercise performed properly was labeled as the Bicep_Correct_Form and the exercise performed abnormally was labeled as Bicep_Wrong_Form, as mentioned in Table 1. For maintaining the good form during bicep curl exercise, the subjects kept the arms aligned to the body, and pointed the elbow toward the ground while lifting the forearm and intensely contracting the bicep muscle at the top of the motion, before slowly lowering the weights back down until the arm was fully extended. In contrast, the bad form was obtained when the subjects were swinging the weights up using shoulders or even leaning back, not bringing the weight all the way down to where the elbow was locked out and dropping the weights very quickly for adding momentum to the impending swing.

4 Dataset

A dataset was generated for this research which consisted of four independent variables and a dependent variable. The first column represented the data acquired from the EMG signals via Myoware muscle sensor. The signals in the dataset captured different types of contractions of the muscle during exercise. When the person exercised in the wrong form, the bicep was stretched abnormally, and the value generated by the signals differed from the values generated by the correct form of exercising. However, anticipating the right form of the bicep only based on the EMG signals was unreliable as every person has different mass of muscle strength. While recording the exercise, some value that was obtained from a body builders' arm during an aberrant movement of the bicep muscle was conflicting with the value acquired from a skinny person's arm during the best form and contraction of their bicep muscle. For tackling this problem, three more independent variables were introduced that dealt with the arms position and orientation [26]. The first, second, and third columns contained the data acquired from the X, Y, and Z axis of the accelerometer. Table 2 lists that Myoware consisted of integer values while the data type of the values acquired from three axes were floating point and the output was an object, representing a sequence of characters.

The accelerometer was placed at a 90° angle on the deltoid muscle. As the exercise began, the sensor started to capture the movement and orientation of the arm. Variant values from the accelerometer were collected during the right and wrong form of the bicep curl exercise [27].

For creating this dataset, ten subjects were selected who were instructed to perform the exercise. The subjects included people having a good built and regular gym-goers, people having a skinny built and who rarely ever exercised, athletes and sports players, and healthy people who aspire to start going to the gym soon. They used dumbbells from 2 kg's up to 15 kg's with which a diverse and adequate dataset was gathered. A data logger script was coded using the Python Serial module with an Arduino nano connected through the USB. Data consisting of 5000 variant values was collected from the Myoware sensor and accelerometer simultaneously using the Python script. Consequently, it was added to the CSV file for using it with Excel and other data analytic tools.

Table 2 Data types of the independent and dependent variables

Column	Data type
Myoware	int64
X-axis	float64
Y-axis	float64
Z-axis	float64
Output	object

5 Results and Discussion

Seven criteria were used for the performances of the ML models as given in Table 3. These were sensitivity, specificity, precision, false positive rate, F1 score, accuracy and classification error where TP, FP, TN, and FN represent the number of true positive, false positive, true negative, and false negative, respectively.

Figure 4 shows confusion matrices obtained by the five ML models on the test set. A confusion matrix illustrates the correctly classified true positive values (first row and first column of the matrix), the false negative values in the appropriate class when they belong in another class (first row and second column of the matrix), the false positive values in the appropriate class when they belong in another class (second row and first column of the matrix), and the true negative values correctly classified in the other class (second row and second column of the matrix).

Table 3 Performance metrics utilized for evaluating the ML models

Measure	Derivations
Sensitivity	TPR = TP / (TP + FN)
Specificity	SPC = TN / (TN + FP)
Precision	PPV = TP / (TP + FP)
False positive rate	FPR = FP / (FP + TN)
F1-score	F1 = 2TP / (2TP + FP + FN)
Accuracy	ACC = (TP + TN) / (P + N)
Classification error	CE = (FP + FN) / (TP + TN + FP + FN)

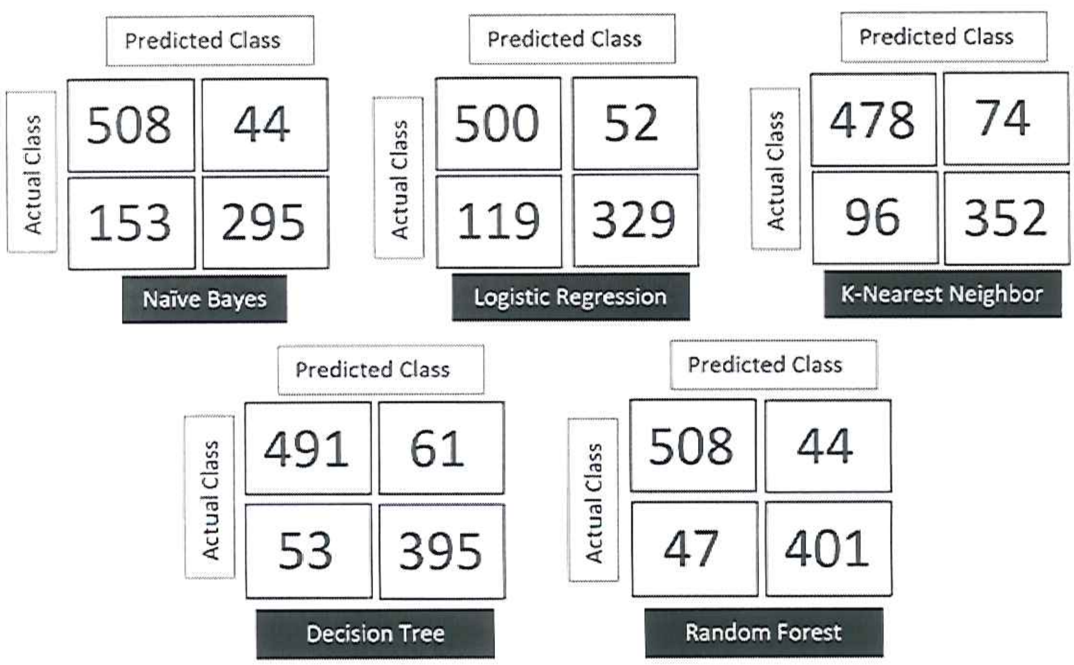


Fig. 4 Confusion matrices of the five ML models

The Naïve Bayes model obtained highest sensitivity due to its precise prediction about the true positive values. However, it had the least accuracy as it is also predicted many false positive values which led to a low total of the true positive and true negative values, decrementing the accuracy of the model. The logistic regression model attained slightly better accuracy than the Naïve Bayes model, but its performance was deteriorated as two of the variables in the dataset were closely inter-related. This condition is known as multicollinearity [28]. Due to this it couldn't significantly surpass the accuracy of Naïve Bayes model.

The sensitivity decreased from Naïve Bayes model to decision tree. The latter model was performing overall well and observed an increase in the true negative values but predicted the positive values fewer than the Naïve Bayes Model.

Random forest classification attained the maximum accuracy of 90.90% and surpassed the rest of the models in all scenarios. This is because random forest trees are learnt on random samples, and random set of features are examined at each node of a tree for the splitting. This causes a diverse and varied relation among the trees. When compared to the decision tree, the random forest performed better as its feature space is split into increased and minute regions.

When setting up the number of trees in an ensemble, the number of trees selected for the model were 10, 50, and 100. By the results obtained from these variations, it was observed that the model was performing best at the selection of 50 trees. It became clear that the number of trees does not always mean the classifier performs better than the previous selection of trees (a smaller number of trees), so doubling the number of trees seems pointless, and in turn would just increase the computational cost [29]. Hence, a high resolution in the feature space can be obtained from diverse and populated trees by selecting the number of trees according to the dataset as increasing the trees further could lead to overfitting.

Table 4 represents the comparison for bicep curl exercise on the dataset obtained from the subjects with regards to ML classification models based on different performance metrics.

According to Table 4, Naïve Bayes and random forest had the highest sensitivity but the low specificity and high FPR for the former were caused due to its high number of false positives. There was a moderate improvement in logistic regression over Naïve Bayes, but this model still had significant false positives when compared to rest of the models. K-nearest neighbor had a slightly better performance than Naïve Bayes and logistic regression as it predicted fewer false positives, however a

Table 4 Performance matrix (all values in %)

ML model	TPR	SPC	PPV	FPR	F1	ACC	CE
Naïve Bayes	92.03	65.85	76.85	34.15	83.76	80.30	19.70
Logistic regression	90.58	73.44	80.78	26.65	85.40	82.89	17.01
K-nearest neighbor	86.59	78.57	83.28	21.43	84.90	83.00	17.00
Decision tree	88.95	88.17	90.26	11.83	89.60	88.66	11.34
Random forest	92.03	89.51	91.53	10.49	91.78	90.90	9.10

low accuracy was acquired due to an increase in the false negatives. The decision tree and random forest models attained a high F1 score due to good precision and sensitivity. These both models had predicted relatively very few false positives and negatives while attaining good number of true positive and negative values. On comparing the models against each other, random forest performed relatively better than decision tree, obtaining an accuracy of 90.90% while decision tree obtained 88.66%. In total, random forest produced the best results, making it the most optimal algorithm for this application problem and dataset.

6 Conclusion

The proposed model for detection of the bicep's form during the bicep curl exercise showed promising results. The EMG signals were recorded from the Myoware muscle sensor placed on the bicep along with the sensory data of accelerometer positioned at a 90° angle on the deltoid muscle for generating a dataset, after which the feature extraction and data preprocessing was performed. Standardization for removing the mean and scaling the independent variables to unit variance was carried out. Also, KPCA assisted in effectively capturing the nonlinear relationships in the data that significantly helped in increasing the performance of the ML model. Five classification models were selected for the comparison of performances based on sensitivity, specificity, precision, false positive rate, F1-score, classification-error, and accuracy. After a comparative analysis, random forest classification proved to be the best fit model performing with an accuracy of 90.90%. Subsequently, a user-end application was designed for displaying the data being recorded by the sensors in real time, and simultaneously storing it in firebase for generating a test set for its deployment in the ML model and exhibiting the performance of a person at end of each session. Hence, this research assists in detecting faults at an early stage and can prevent long-term effects due to wrong form and posture.

In the future work, the presented model can be used in applications that can accelerate research and development of low-cost system designs and immensely cut-down the time and cost required for commercial and expensive productions. It can shorten the time for validating new types of EMG and muscle-based devices which is especially important given rapid advances in the material.

We aspire that the positive and conclusive results obtained from this work can be leveraged and further be improvised by data scientists and researchers to stimulate the advancement of highly accurate yet practical ML solutions for detecting muscle deformities from reliable and low-cost system designs and formulate immense innovations in health and fitness domains.

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