Exercise Pattern Prediction

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ABSTRACT

Exercising regularly is essential for both physical and mental well-being. In this era of desk jobs, we barely should spend more time exercising. This will not only keep us physically fit but also mentally fit. There are various forms of exercise that a person can do at home. These exercises must be done correctly because if they are not done correctly, it can lead to various bone aches. These exercises must be done under the supervision of instructors so that we know how to do the exercises correctly. But hiring an instructor can be expensive. So in our study, we tried to identify if a person is doing Unilateral Dumbbell Biceps Curl properly or not. Sensors were attached to the users' body parts and in equipment through which passive sensor reading was taken. We then applied machine learning models and tried to predict if the user was correctly performing the exercise or not.

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Chapter 1

Introduction

Exercising regularly leads to numerous benefits, both physically and mentally. It reduces the risk of high blood pressure, heart disease, diabetes, obesity, and more. Apart from the physical advantages, it also combats stress and anxiety [5]. Weight lifting is one of the most common exercises a person can frequently do at home. Weight lifting allows us to keep our bones strong and healthy as we start losing bone density by a tiny fraction after we become older than 30. It also helps improve posture, sleep, mood, and energy levels [6]. Free weight exercises are the cause of 90.4 % of injuries associated with weight training. Incorrectly lifting weights can lead to sprains, strains, fractures, and other painful injuries [7].

A possible way of avoiding such injuries is hiring a personal instructor who will point out if the users are making any mistakes. This mistake can be in body movement, posture, etc. Hiring an instructor can be very expensive and is also not always available. In our study, we will try to predict if a user performs Unilateral Dumbbell Biceps Curl passive sensors correctly. This avenue is much cheaper than scalable than hiring instructors. Previous studies have used four sensors attached to the equipment to classify if the user is correctly performing the weight lift.We are proposing to use less number of sensors and obtain a good model.

The previous study did not focus much on the machine learning approach. They only used the random forest model and obtained an accuracy of 80%. In our study, we achieved an accuracy of 86.20% using random forest. For other models, like Support Vector Machine, Decision Tree, Random Forest, Gaussian Naive Bayes, and K Nearest Neighbour, we obtained 74.3%, 67.92%, 86.20%, 57.62%, and 70.5% accuracy, respectively. We also explored the performance of other machine learning models. We have also explored other performance metrics like receiver operating characteristic curve, confusion matrix, etc. The previous study did not focus much on data preprocessing, feature selection, or hyperparameter tuning. We filled all those gaps in our work.

Chapter 2

Literature Reviews

There are very few study publications on this topic from some researchers that sought to investigate this area.

There are relatively few research have examined the topic of how an activity is carried out "well." The exercise used in Velloso, E., Bulling, A., Gellersen, H., Ugulino, W., Fuks, H.[1] was a unilateral dumbbell biceps curl. In other words, lifting weights with just one hand. To forecast how successfully the activity is performed, they have used data from a variety of sensors. Six men in total were enlisted to help with data collection. The users' bodies and their equipment both have sensors attached to them. The sensor's readings included roll, pitch, yaw, total acceleration, etc. Numerous statistical features that define the sensor readings of a window were generated using this data. In order to create a machine learning classifier, Random Forest was used.In training data, the overall accuracy was 98.2%. On test data.78% of accuracy have been achieved.However, the study has lots of scopes for improvement. Include female participants to create a more generic classifier that works for both male and female.

The design, implementation, and assessment of FEMO, a passive RFID-based free-weight activity monitoring system, are presented by Ding, H., Shangguan, L., Yang, Z., Han, J., Zhou, Z., Yang, P. Zhao, J.[2]. In this work, the training tools are passive RFID-tagged dumbbells. The four fundamental modules that made up the implementation of FEMO are Doppler value pre-processing, activity segmentation, activity recognition, and activity assessment.FEMO uses the backscattered signal for on-site activity recognition and assessment. The outcome of in-depth tests conducted on 15 volunteers shows that FEMO may be used for a range of free-weight exercises and can provide helpful feedback for users' activity correction.The algorithm of FEMO is unable to deal with non-stop activities, as a result the accuracy of the segments will reduce to some extent. So, it is clear that the implementation is not feasible at all.

Lee, M.W., Khan, A. M., Kim, T. S.[3],,demonstrating a single tri-axial accelerometer-based PLL (Personal Life Log) device that can recognize human activity and generate information on exercise. Using subject-independent and subject-dependent recognition for the six everyday activities of lying, standing, walking, going up and down stairs, and driving, the PLL system was evaluated on a total of twenty subjects. Electronic tools like video sensors (like cameras) and motion sensors are used to record life logs. Artificial neural networks (ANNs), based on the feed-forward back-propagation algorithm, are used as a classifier after computing the feature vector for each level. Subject-independent recognition accuracy was 94.43 %, while overall subject-dependent recognition accuracy was 96.61 %. Even though they utilized a laptop for their feasibility study, it would be preferable to develop a PLL system that is more portable and less constrained. The user would feel more comfortable and the outcomes would be better if the PLL system was used with a mobile phone.

Kotsev, G., Nguyen, L. T., Zeng, M., Zhang, J.[4], they have have analyzed a dataset that had been collected from thousands of users. They have shown graphs amount of user activity changes through out the year. They have shown simple graphs of how activity level across various country. From the results of these graphs, they have tried to draw conclusions of why these changes occurs. Using the data, they have also tried to predict the future activity level of the users based on time series. The results they have obtained is very poor, and the highest accuracy was only 53% using the Logistic Regression Model. This study is very poorly done, the only thing they did was used an existing dataset to draw simple graphs and tried to derive conclusions from it.

Chapter 3

Data Collection & Processing

The dataset was collected from a Kaggle. The dataset has 40000 data and 160 features. The data was taken from a total of 4 and each sensor took a reading of Roll, Pitch, and Yaw in all three x y and z directions. Additionally, it measured total acceleration, and also took readings from gyro sensors.

3.1 Readings from sensors

Pitch is a rotation around the vertical axis. Roll is a rotation around the front-to-back axis.Yaw is a rotation around the side-to-side axis. A gyroscope is a device that can measure and maintain records of an object's orientation and angular velocity. Magnet represents the magnitude of the geomagnetism and magnetism generated by a magnet. Total acceleration refers to how quickly the sensors move. Six participants will wear accelerometers on their belts, forearms, arms, and dumbbells to collect data and They provide several types of measurement. The number of windows refers to how many times participants are lifting dumbbells. Five different ways to complete a set of 10 unilateral dumbbell biceps curls were requested of the participants. When a participant performs exactly as required by the specification, class A is assigned. Class B is assigned when participants in the group throw their elbows forward. Lifting the dumbbell only halfway those are assigned Class C. Those who only lower the dumbbell halfway are given Class D. And participants in a group are given Class E when they throw their hips forward. Class A represents how the activity should be carried out, whilst the other 4 classes often make mistakes. The raw time is calculated using Unix time. A system for displaying a point in time is known as Unix time. It is the number of times that have passed from January 1st, 1970 in seconds.

3.2 Derived Features

Maximum: Maximum sensor value of a particular sensor reading belonging to a specific window. **Minimum:** Minimum sensor value of a particular sensor reading belonging to a specific window. **Standard deviation:** Standard deviations are used to determine how variable a distribution is. The standard deviation for each attribute is measured. **Average:** Average is a number that represents the center or typical value in a group of data, specifically the mode, median, or mean, which is derived by dividing the total number of values in the set by their sum. **Amplitude:** Amplitude is the difference between maximum and minimum values. All the maximum and minimum values are calculated from sensor value. **Kurtosis:** The combined weight of a distribution's tails in relation to its center is measured by kurtosis. A bell peak with the majority of the data being within three standard deviations (plus or minus) of the mean can be seen when a collection of essentially normal data is graphed using a histogram. **Skewness:** Skewness is a measure for a distribution's asymmetry. When the left and right sides of a distribution are not mirror reflections, it is asymmetrical. Right (or positive), left (or negative), or zero skewness can all apply to a distribution.

3.3 Data Visualization

This section contains some visualizations of the data. The first diagram (figure 3.1) visually represents readings from sensors against time. The second diagram (figure 3.2) shows that our dataset is imbalanced. We attempted to handle that situation using oversampling but it didn't work well for us so we dropped that method. The third diagram (figure 3.3) shows how much data was collected from each of the 6 users. The fourth diagram (figure 3.4) shows how the average pitch value of the forearm sensor varies for each class. The fifth diagram (figure 3.5) shows how the minimum pitch value of the forearm sensor varies.

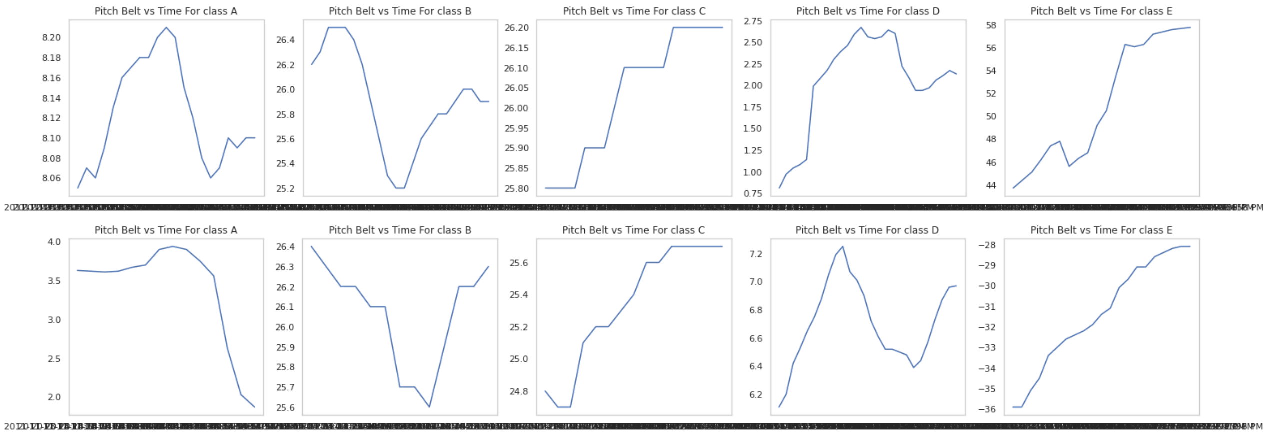

Figure 3.1: Readings from sensors of different classes

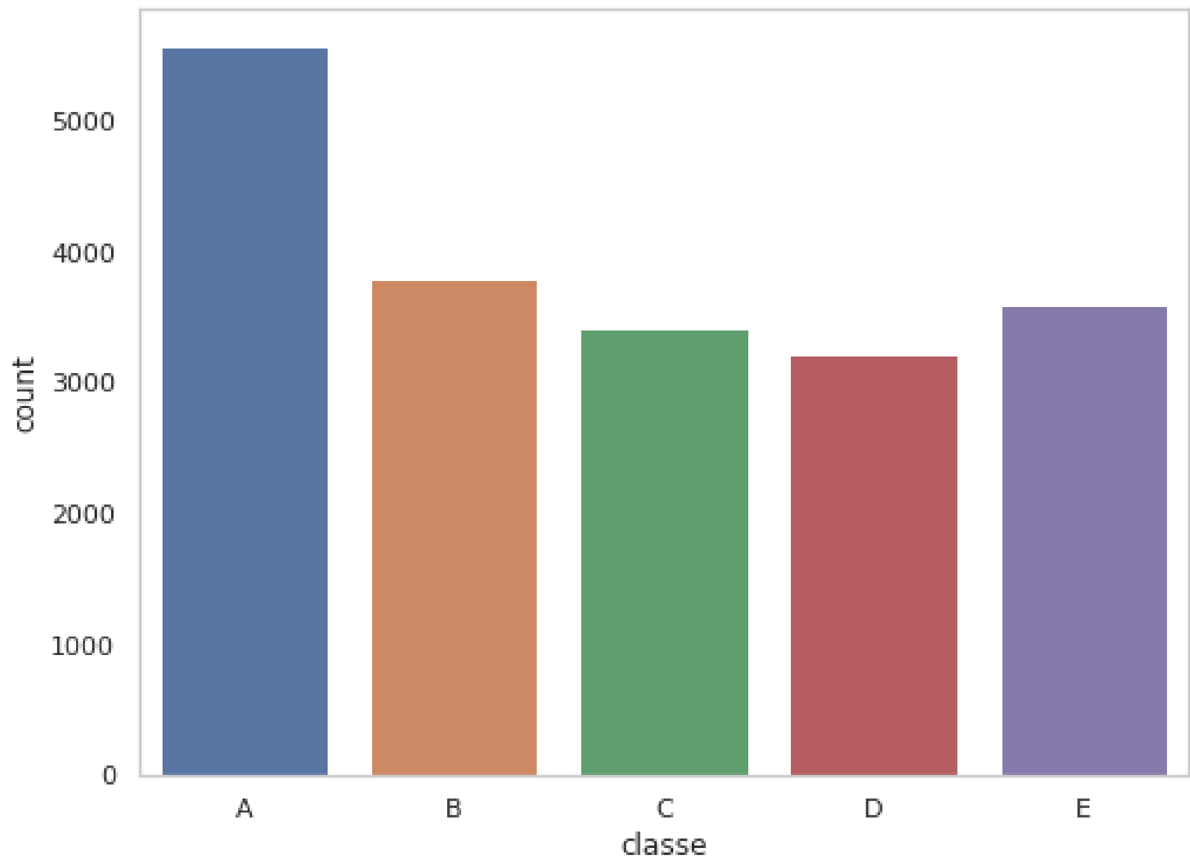

Figure 3.2: Target Class Distribution

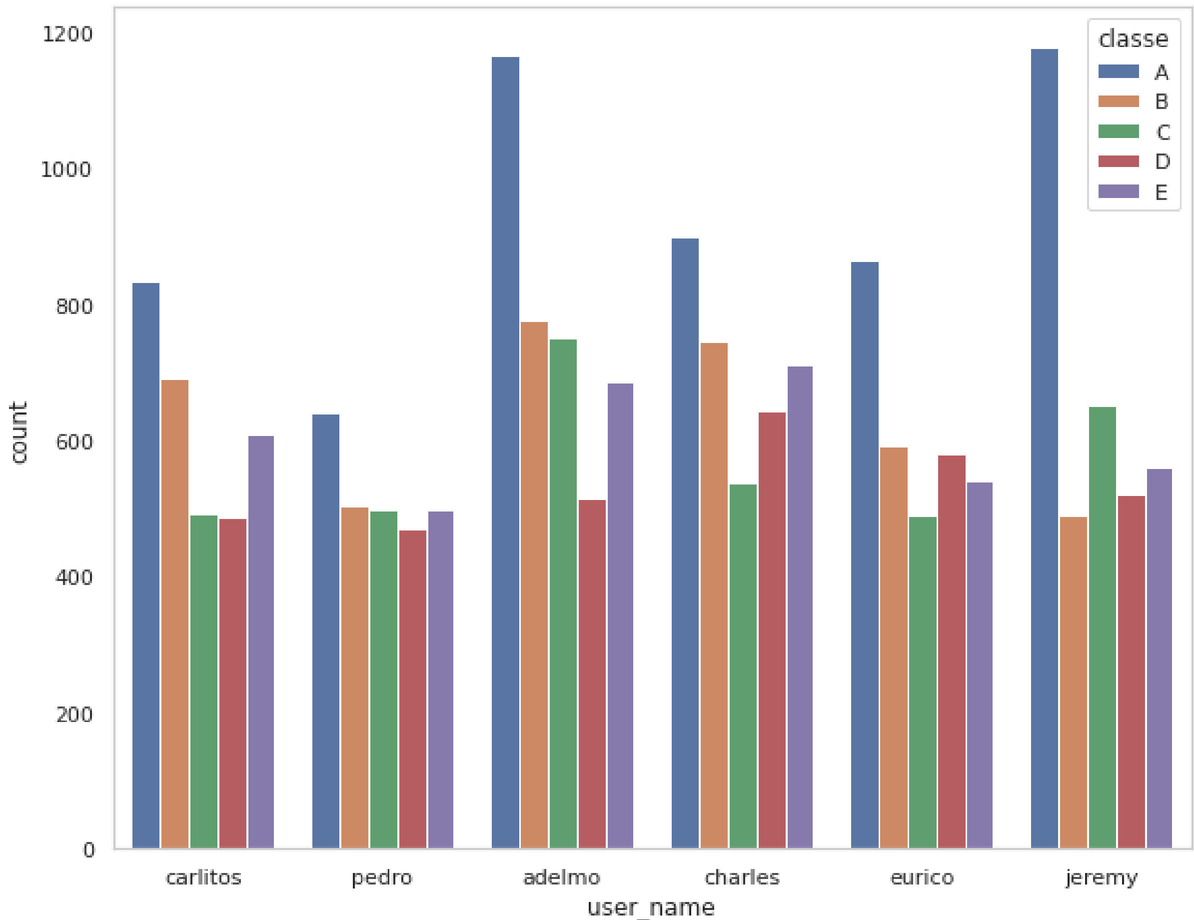

Figure 3.3: Target Class Contribution from Each User

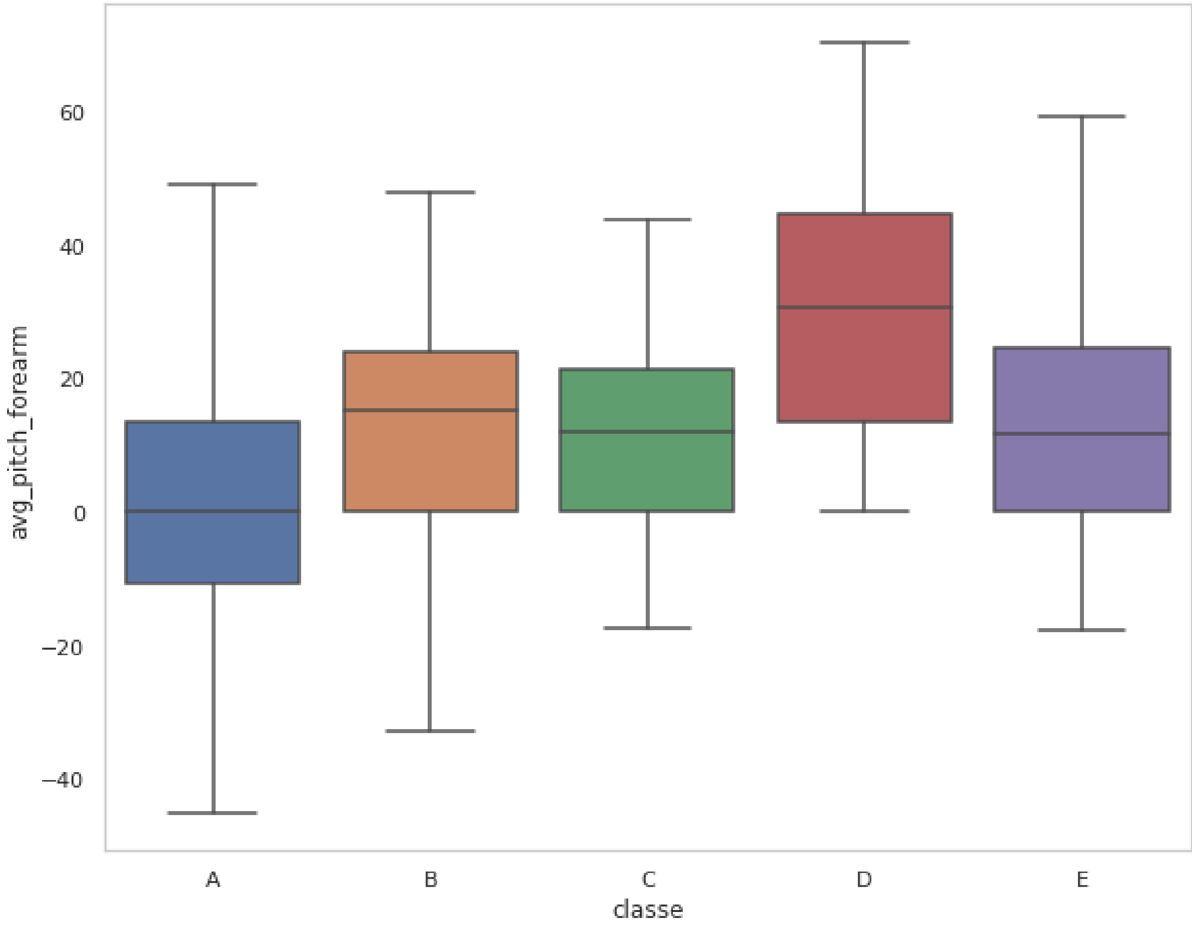

Figure 3.4: Average Pitch for Forearm sensor

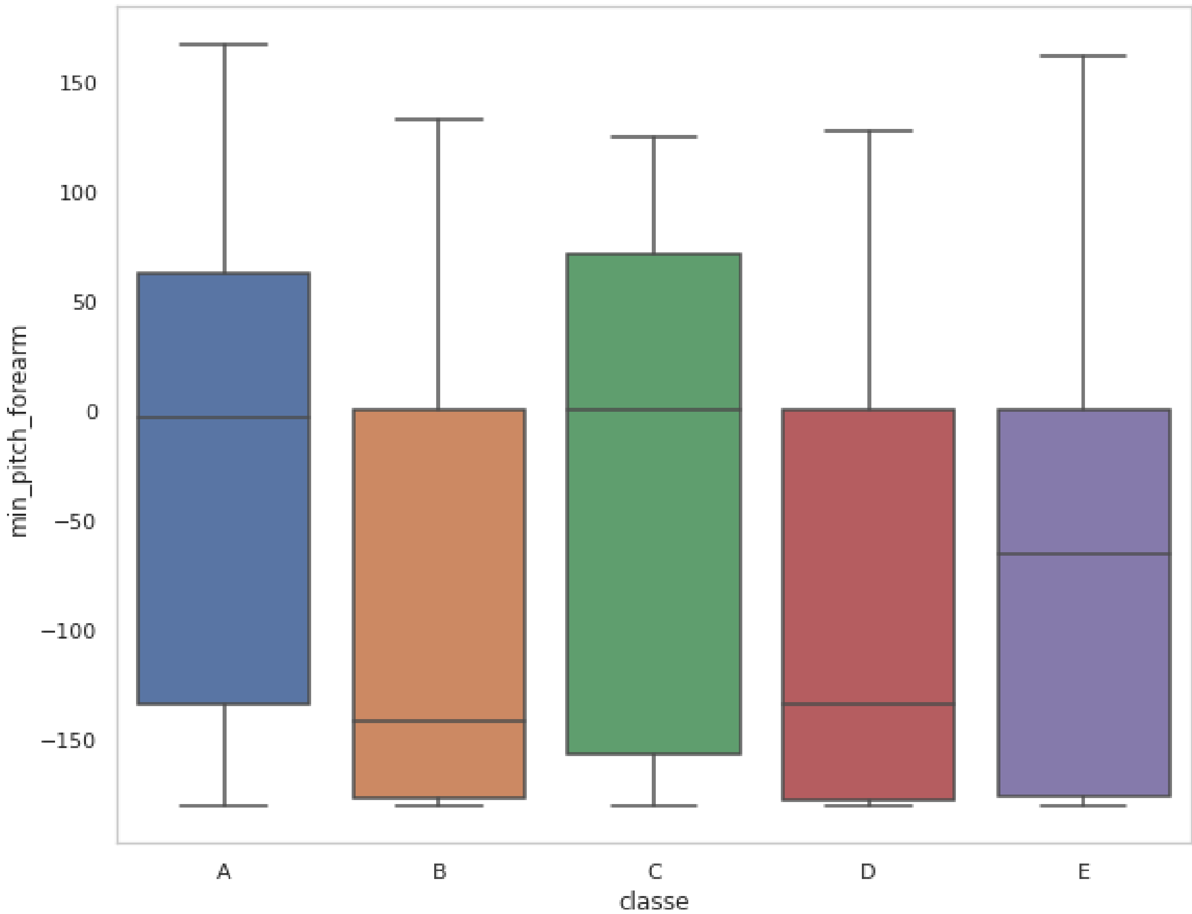

Figure 3.5: Minimum Pitch for Forearm sensor

3.4 Preprocessing

We preprocessed the file as usual by filling in missing values. The dataset contained lots of derived features initially, but most of those features were empty. So, we first had to fill in those missing values. The derived features are all statistical, so filling them was quite easy. It was easy because Pandas library has it filled. Apart from these, we have also used a standard scaler to scale all the values, and finally, all the values are between -1 to 1. The dataset was also imbalanced. To handle this, we used the synthetic minority oversampling technique. But, the performance of the models decreased when oversampling was used. So we removed it.

Chapter 4

Methodology

4.1 Working Procedure

Our workflow is defined using the following diagram. We first collected data from Kaggle. Data visualization was performed on the data to show patterns among different exercises. In feature extraction, many features were derived using the raw sensor data. We derived many features and a total of around 160 features. As the extracted features contained missing values in the original dataset. We had to fill them out before moving on to the next phase. Then as there were many features, we needed to minimize them. To perform feature selection, we used two approaches. First, we measured Pearson correlation. Among them, we kept features with an r value greater than 0.05 and lower than -0.05. Finally, we number of features dropped to 58. We then fed this data to our model. We performed another feature selection which is One-way Anova or also known as the f-test. To make a fair comparison, we also choose 58 features using the f-test. We then compared the performance of the models using these different feature selection approaches. To evaluate the performance of the models, we used accuracy measures, a confusion matrix, and AUC ROC Curve.

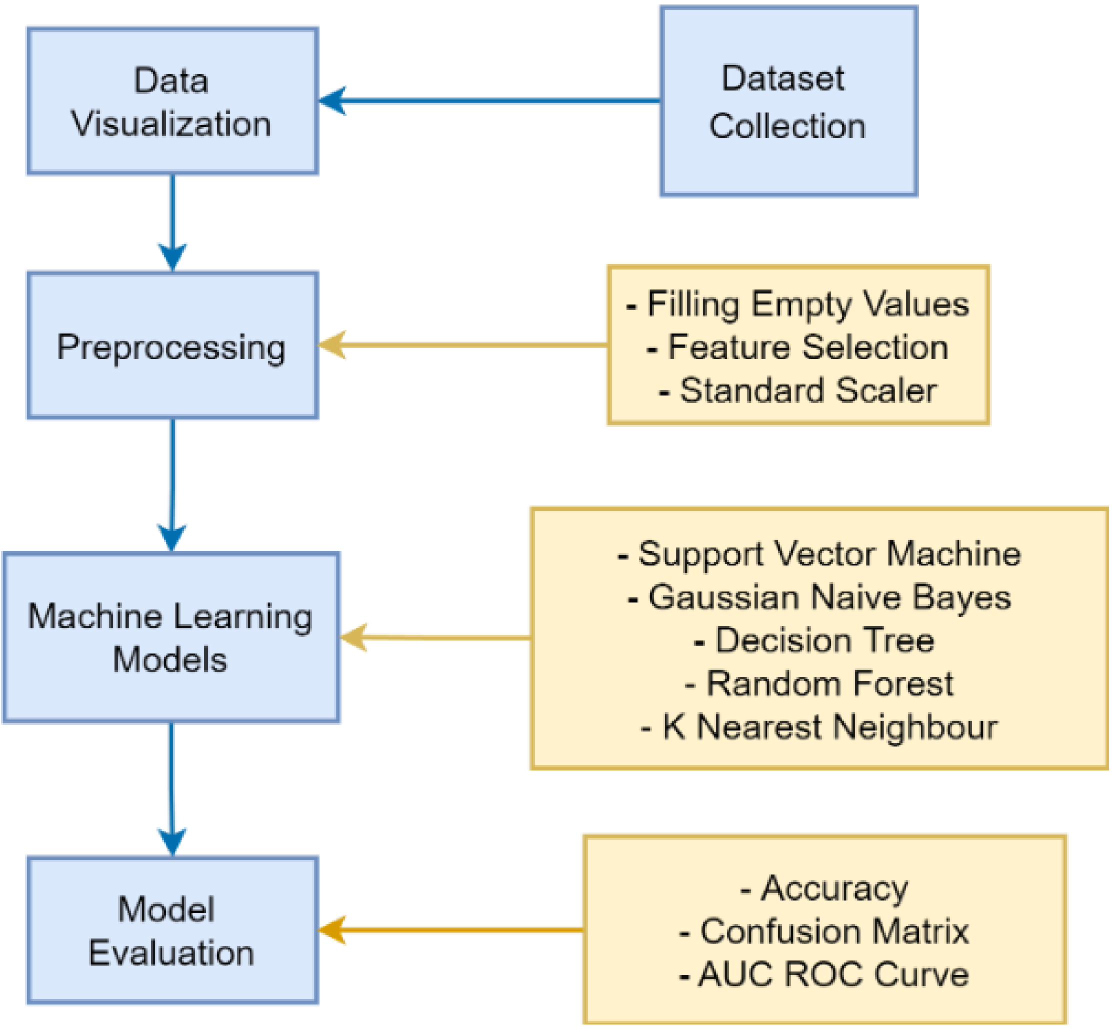

Figure 4.1: Workflow

4.2 Feature Selection

We did two types of feature selection, the first one was using Pearson Correlation and the second one was f-test or One way ANOVA. Before performing the feature selection, we manually removed many columns using our domain knowledge. There are some columns that have only direct readings from the sensors. The machine learning model cannot learn anything meaningful from these data. So we removed them first. Then we performed the other feature selections.

4.2.1 Pearson Correlation

We encoded the target column first as Pearson Correlation can only be used for numeric values. We calculated the Pearson correlation value r, for all features with the target column. Then, we only kept the values that showed somewhat correlation. We kept features that had values of r greater than 0.05 or less than -0.05.

4.2.2 One-way ANOVA / f-test

We used the in-built sci-kit learn library to perform the f-test. Since for Pearson correlation, we used a total of 58 features, and we have also selected the best 58 features according to the f-test. The one-way ANOVA compares the mean between the groups and determines whether any of those means are statistically significantly different from each

Chapter 5

Experiments and Results

5.1 Model Performance (Accuracy)

The summary of our findings is shown in table 1. From the table, we can see using the features selected using F-test, we obtained a better model in 4 out of 5 cases. We can also see the best performing model is Random Forest Classifier. This is because Random forests are great with high dimensional data since we are working with subsets of data. It is faster to train than decision trees because we are working only on a subset of features in this model, so we can easily work with hundreds of features. Decision trees, as usual, don't show much good performance. K nearest Neighbour is not as good as a Random Forest because it treats all the features equally. From the Pearson correlation values that we have seen in feature selection, some features contribute more than others. Random forest takes those things into account. Random Forest doesn't treat all features equally. For some features it can separate the data better so works well. Also, SVM is performing well as the dimension of our data is quite high. These are the reasons why SVM is working well. Also, we didn't tune the value of k in K nearest neighbor, tuning it would increase its performance. We have used Gaussian Naive Bayes instead of just Naive Bayes because Naive Bayes works for categorical data only. Whereas Gaussian Naive Bayes is made to handle continuous data.

Name of Classifier	**Pearson Correlation**	**F-tests**
Decision Tree Classifier	64.76%	**67.62%**
Random Forest Classifier	**86.20%**	83.33%
Gaussian Naive Bayes	56.20%	**57.62%**
K Nearest Neighbour	67.62%	**70.5%**
Support Vector Machine	72.3%	**74.3%**

Table 5.1: Accuracy of the machine learning models for two different feature selection approaches.

5.2 Confusion Matrix

The confusion matrix for all the models is provided below. Except for Random Forest, the remaining 4 confusion matrices are for models whose feature selection was done using F-test.

Target Column	Precision	Recall	F1-score
E	0.94	0.91	0.93
D	0.63	0.81	0.71
C	0.88	0.84	0.86
B	0.89	0.78	0.83
A	0.87	0.92	0.89

Table 5.2: Confusion Matrix for Random Forest

Target Column	Precision	Recall	F1-score
E	0.81	0.76	0.79
D	0.35	0.43	0.38
C	0.65	0.70	0.67
B	0.71	0.59	0.65
A	0.63	0.65	0.64

Table 5.3: Confusion Matrix for Decision Tree Classifier

Target Column	Precision	Recall	F1-score
E	0.90	0.82	0.56
D	0.55	0.86	0.67
C	0.67	0.70	0.69
B	0.89	0.65	0.75
A	0.73	0.77	0.75

Table 5.4: Confusion Matrix for SVC

Target Column	Precision	Recall	F1-score
E	0.95	0.62	0.75
D	0.22	0.10	0.13
C	0.45	0.80	0.58
B	0.56	0.67	0.61
A	0.71	0.48	0.57

Table 5.5: Confusion Matrix for Gaussian Navie Bayes

Target Column	Precision	Recall	F1-score
E	0.84	0.79	0.82
D	0.44	1.00	0.61
C	0.66	0.66	0.66
B	0.89	0.49	0.63
A	0.79	0.77	0.78

Table 5.6: Confusion Matrix for K Nearest Neighbors

5.3 AUC ROC

For the best performing model in our dataset, which is the Random Forest. We plotted an AUC ROC curve for it. Since we are dealing with a multi-class problem. We used the One Vs Rest approach. Here, for each class, we drew a ROC curve.

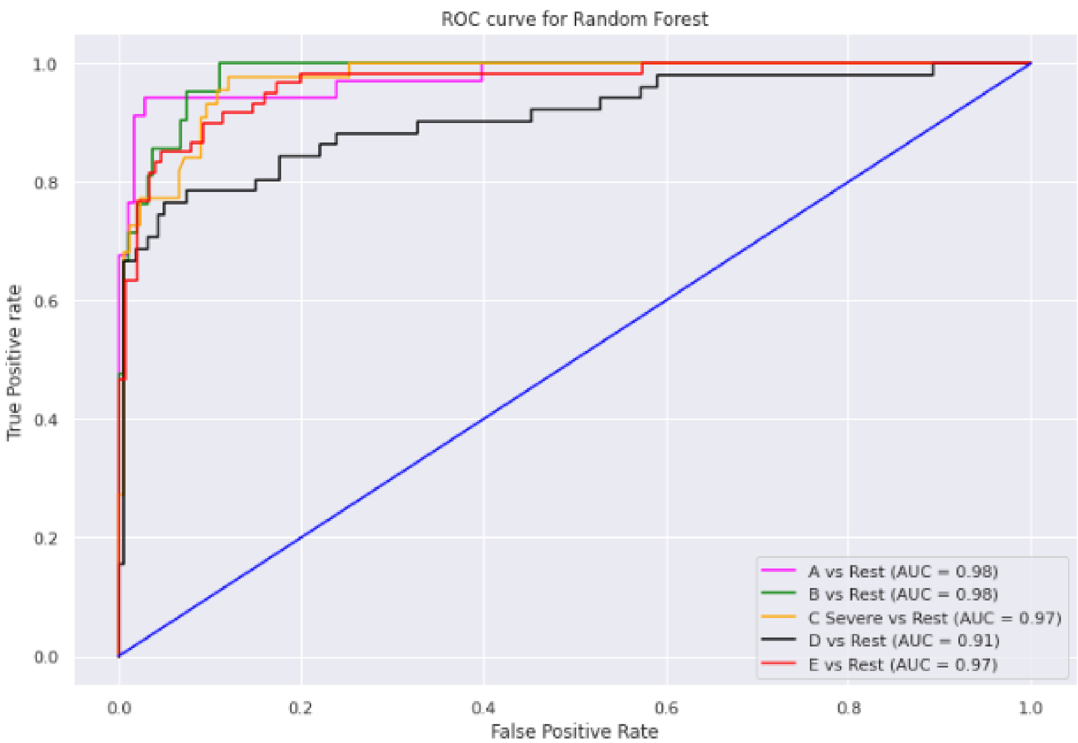

Figure 5.1: AUC - ROC curve for Random Forest

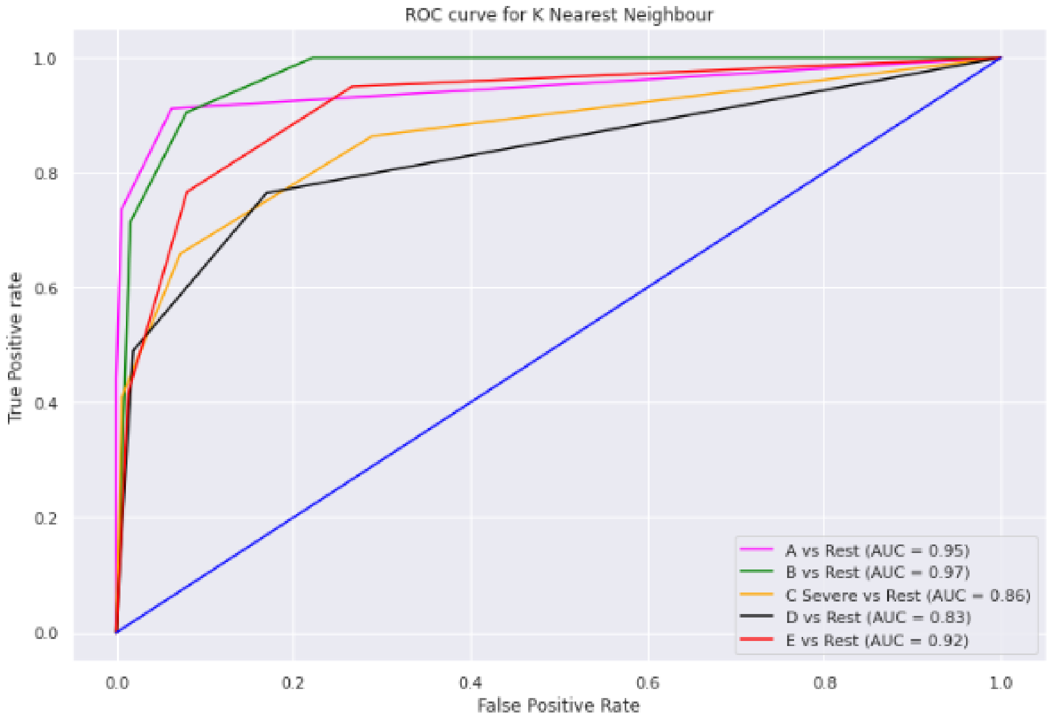

Figure 5.2: AUC - ROC curve for K Nearest Neighbours

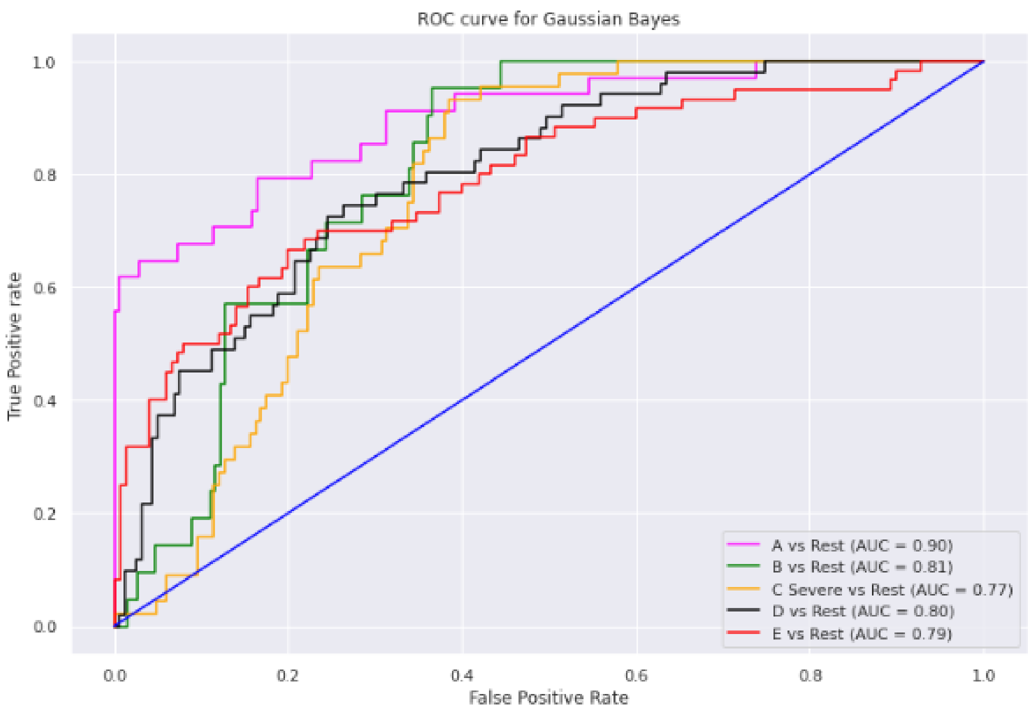

Figure 5.3: AUC - ROC curve for Gaussian Naive Bayes

Chapter 6

Future Work and Conclusion

6.1 Future Work

We'll use a Bluetooth sensor for more appropriate usage. The mobile phone will get sensor data through Bluetooth. The user may observe how to lift a dumbbell properly through a mobile phone. We'll use more sensors, including magnetometers, gyroscopes, and orientation sensors. A device that measures magnetic dipole moment is called a magnetometer. Gyro sensors are tools that detect angular velocity. A device's orientation in relation to an orthogonal coordinate frame is determined via an orientation sensor. Users will receive more precise output from these sensors. Many attributes may be derived from those sensors. Hyperparameters describe important aspects of the model, such as its complexity or how quickly it should learn new data.

6.2 Conclusion

Regular exercise has a variety of advantages for the body and mind. Lifting weights improperly can result in fractures, sprains, strains, and other painful injuries. Four sensors attached to equipment in earlier trials were used to determine whether the operator carried out the weight lift appropriately. The users may get uncomfortable and unable to exercise freely if several sensors are attached. We propose using fewer sensors to get a good model. The machine learning method was not highly emphasized in the previous study. Their accuracy was 80% when they only used the random forest model. In our study, we achieved an accuracy of 86.20% using random forest. We obtained 74.3% and 70.5% accuracy for other models like Support Vector Machine and K Nearest Neighbour, respectively. A receiver operating characteristic curve, a confusion matrix, and other performance metrics were also explored.

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