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AI-based ACL Exercises Recognition System Using Wearable Multi-Sensor Data Fusion

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A B S T R A C T

Human activity recognition has attracted researchers' attention in the last two decades. Anterior Cruciate Ligament (ACL) exercises are example of these activities that have to be performed correctly to ensure efficient knee joint recovery. Hence, Machine and Deep Learning algorithms have been employed to classify ACL exercises and evaluate its correctness. This study investigates the accuracy of five machine learning algorithms, SVM, Decision Tree, Random Forest, Gradient boosting and KNN, with CNN in terms of their ability to classify ACL exercises. The data of seven ACL exercises, performed by four subjects, were collected using Accelerometer and gyroscope sensors, then these data were used to train the algorithms. Results showed that both CNN and Random Forest models performed well and achieved higher accuracy among the other algorithms with real accelerometer and gyroscope data. However, Random Forest model outperformed other models when relying on real accelerometer data only or with synthesized data. Moreover, it is also found that gyroscope data are essential for such systems to train the algorithms efficiently and excluding such data leads to downgrade the classification performance.

Introduction

The Anterior Cruciate Ligament (ACL) is an essential part of the knee joint that plays a crucial role in joint stabilization. Frequent strikes to ACL compromises the person's quality of life due to its direct impact on knee function and eventually on individual's mobility [1]. Athletes involved in sports such as football and basketball are more susceptible to ACL injuries than others, and hence effective exercises are prescribed to prevent potential further injuries and ensure knee stabilization [2]. Once the ACL is injured, specific recuperation exercises are advised based on the phase of injury [3-4]. The ACL recovery process goes through three recuperation phases to ultimately restore knee function effectively. First phase or so-called early-phase enhances the range of motion of the knee joint by activating the related muscle. Heel slides and quadriceps are examples of early-phase exercises. Middle phase or intermediate-phase follows the early-phase and is aimed to strength the knee muscles by performing intensive exercises such as squats, leg presses and step-ups. Final phase is dedicated to ensure fully functionality of the knee joint that allows the individuals return to their daily activities. Exercises that include speed and force are performed in this phase, such exercises ensure re-gaining the muscle power [3-4].

In recent years, specific standalone sensors such as accelerometers, gyroscopes, Global Positioning System (GPS) and cameras are being used to recognize the human activity. These sensors are mostly attached to individual's limbs to identify the human actions and ultimately evaluating its correctness [5-6]. For instance, ACL recuperation exercises have to be performed correctly to accelerate the recovery process of the knee ligament. However, patients often incorrectly perform the ACL exercises that lead to prolong the recovery procedure. Hence, therapists are needed to guide the patients throughout exercises performance which consumes time and tools for both therapists and patients.

Moreover, there has been a growing interest on utilizing Artificial Intelligence (AI) and Machine Learning (ML) technologies across various medical fields including orthopedic surgery and ACL [7]. Consequently, ML algorithms have been employed to distinguish ACL recuperation exercises and ensuring correct and effective performance of the exercise in a real-time manner. Several studies have discussed the effectiveness of the ML techniques in distinguishing the ACL exercises [8]. For example, Support Vector Machine (SVM) was used to distinguish ACL exercises based on the information collected form accelerometer and gyroscope sensors [9]. According to this study, accurate classification of ACL exercises was achieved using SVM model, and the model showed high performance against noise. However, the computational process is compromised in large datasets which is considered a challenge in real-time applications [10]. Random Forest algorithm was also used to identify ACL exercise, this technique showed an effectiveness in processing various data that were collected from wearable sensors on different patients [11]. Although that Random Forest is well-known in handling large datasets and reducing overfitting, this technique is relatively slower in predicting the exercise than other simpler techniques [12]. Moreover, data collected from motion capture systems was classified using K-nearest Neighbors (KNN) model to identify ACL exercises. KNN model has shown an accurate classification when handling small datasets. Large datasets, however, forces the model to calculate the distance to other points in the datasets and ultimately compromises the computation process [11].

Deep learning (DL) models, such as Convolutional Neural Network (CNN), have also been employed to classify ACL exercises. Video stream was used as an input data and the CNN was trained to classify the exercises based on the acquired images. According to this study, high accuracy was achieved in distinguishing ACL exercises using CNN model. However, CNN models require large datasets to train the model effectively and distinguish the variance between patients [13].

This paper tests five well-known ML algorithms with one deep learning algorithm and compares their accuracy in recognizing ACL exercises. Identifying the optimum ML model enhances the recuperation process by providing real-time feedback for the exercise. The rest of the paper is arranged as follows: next section explains the materials and methods that were used to implement the study. Section 3 discuss the results and identify the most suited technique for ACL exercises recognition. Section 4 concludes the results with suggestions to future works.

Methodology

This section describes the implementation of the ACL recuperation system which consists of two parts: the sensor data fusion and classification models. Fig.1 shows the flow of the system starting by collecting the data and ended by the ML classification model.

The date was collected using two Inertial Measurement Units (IMUs) model (MPU6050 sensor) in order to produce more accurate and reliable information rather than using single sensor. These measurement units are connected to a custom-designed microcontroller board (Arduino) that characterized by having 3-axis gyroscope and 3-axis accelerometer which allow us monitoring the leg movement in all direction [14].

Figure 1: Schematic diagram of the proposed framework for the ACL recuperation system.

The two IMUs were placed on thigh and shank with an elastic band in order to measure the angles and orientations of the exercises through the three axes of movement (along the X, Y, and Z axes) as shown in Fig.2. Such configuration is advisable to record the leg's orientation in various movements and ultimately can be recognized by machine and deep learning models because of most ACL exercise specially ones used in this study can be achieved using this position. It should be noticed that the two sensors (accelerometer and gyroscope) were tied to the thigh and shank using elastic bands. Such attachment is essential to prevent sudden movement that could affect the acquired data from the two sensors [15]. Moreover, this wearable system was designed to provide feedback on a set of common ACL recuperation exercises, including straight leg raises, heel slides, step up/down and knee stabilization. Next paragraph explains how the data were collected and preprocessed for the purpose of ACL exercises classification.

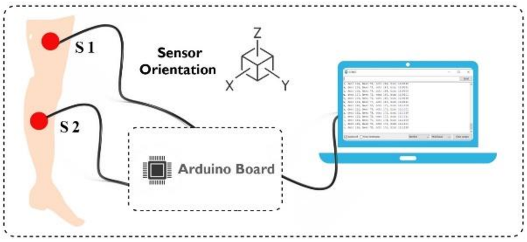


Figure 2: MPU6050 sensors placement and hardware configuration

Microcontroller, Arduino Integrated Development Environment (IDE), was used to continuously collect the data from the two measurement units, where the data was sampled at a frequency of 1k Hz. Moreover, the collected data was streamed as a time-series in a real-time manner and saved in the personal computer as a comma-separated values (CSV) files for further analyzing and processing in order for the models to be trained properly. Four male subjects, aged 38 ± 2 years, have participated in the experiment, where their consent was taken prior the experiment initiation. The participants in this study have had experiences with sports injuries, including ACL injuries. They were asked to perform seven different ACL exercises as shown and described in Fig. 3 and table 1. Table 1 clearly describes how the ACL exercises were performed in terms of repetition and duration. These exercises have previously investigated and proven to have a direct positive impact on ACL recovery. In particular, the seven exercises cover the functional movements of the knee, which ultimately improves the rehabilitation strategies in clinical practice. Moreover, such exercises positively effect on ACL recovery process by targeting the core muscles and ligaments in terms of restoring strength, improving knee controlling and providing a wide range of motions [16].

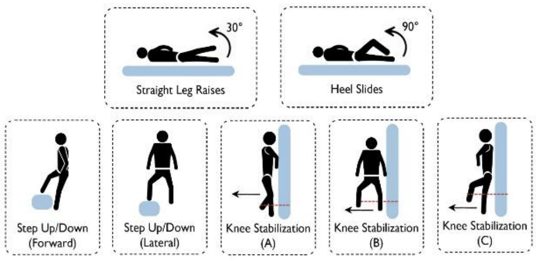


Figure 3: Selected exercise in the recuperation process of ACL post-surgery

Table 1: The list and description of the utilized ACL recuperation exercises.

Exercises ID	**Exercise characteristics**		
	Names	**Repetitio No.**	**Guidelines**
E-1	Straight Leg Raises	10	Leg raises → hold 10s → leg down 3s
E-2	Heel Slides	10	Leg bends 90 degrees → 0 degrees
E-3	Step Up/Down: A	25	Forward step-up working leg → backward step-down the operative knee
E-4	Step Up/Down: B	25	Lateral step-up working leg → lateral step-down the operative knee
E-5	Knee Stabilization: A	25	Move leg backward at 45 degrees → hold for 5s → relax for 5s
E-6	Knee Stabilization: B	30	Move leg laterally outward → hold for 5s → relax for 5s
E-7	Knee Stabilization: C	30	Move leg forward at 45 degrees → hold for 5s → relax for 5s

For instance, straight leg raises exercise activates the quadriceps muscles, while heel slides improve knee's flexion and extension that ultimately improve knee flexibility. Furthermore, knee stabilization, step up and down exercises are essential for daily life activities and enhances the neuromuscular control of knee joint [17].

The collected data was preprocessed through several steps starting by visually exploring the data and ensuring that there is noticeable difference between them. Secondly, the raw data was normalized and cleaned to eliminate the empty bins and wrong format data if exists. Data normalization is an important preprocessing step as it improves the performance of ML models by ensuring similar scale for extracted features [5]. Finally, the cleaned data were labeled and assigned manually based on the exercises' identifications as shown in Fig.3.

To recognize activities, five well-known ML algorithms and (CNN) were used in this experimental study to compare their performance and accuracy in classifying the appointed ACL exercise. The ML algorithms are SVM, Decision Tree, Random Forest, Gradient Boosting and KNN. These algorithms handle both classification and regression problems, so they could be used to recognize the ACL post-surgery exercises easily. For instance, SVM is widely used for supervised learning algorithm and could be effectively applied to ACL exercises recognition [18] while Decision Tree is easy to implement for such tasks [19]. Moreover, Random Forest algorithm reduces the overfitting and combines multiple decision trees output for classification improvement purposes [20]. On the other hand, Gradient Boosting can capture complex patterns in the collected data, so it is necessarily to check its performance among the others [21]. Finally, KNN algorithm is a non-parametric, supervised learning classifier. It is considered one of the most popular and simplest ML classifiers [22]. Moreover, a deep-learning model Convolutional Neural Network (CNN) has also been used in this study for comparison purposes which is widely used in this filed as mention earlier. Namely, CNN has been examined and showed good performance in classifying ACL and human activities recognition due it is ability to capture key features of time-series signals such as frequencies and amplitudes [23-25].

Furthermore, to reduce computational resources and ensure efficient training, data augmentation techniques were employed with small dataset in the experiments in order to enhance model generalization and increase the diversity of training samples. Data augmentation in time domain were used to synthesize new samples based on the existing data. These techniques were considered to fulfil to two critical issues, firstly data augmentation enhances the robustness and diversity of training datasets. Secondly, synthesizing new data were suggested to overcome the potential problem of limited dataset and ultimately improves the performance of classification models. Specifically, transformations methods including amplitude warping and noise addition (scaling and jittering) were used to generate more data samples in order to address data insufficient issue. These techniques are widely used in time series data including human activity data. Amplitude warping involves applying non-linear transformations to the amplitude of the data over time while noise addition involves adding random noise into the signal such as Gaussian noise or white noise [26][27].

Results and Discussion

In this study, five ML and CNN algorithms were compared in terms of their performance and accuracy to classify seven ACL Exercises. Firstly, it was necessary to make sure that all exercises were performed in a similar manner by the subjects. Therefore, the correlation coefficient was calculated for each exercise between the four subjects. Considering that two sensors were used to record the leg's movement and each sensor gives 6 types of data (3 for accelerometer and 3 for gyroscope), hence 12 readings were obtained at each sampling for the appointed exercise. To simplify the correlation calculation, the mean of the 12 readings throughout the exercise's duration was calculated giving a time-series of 12 values.

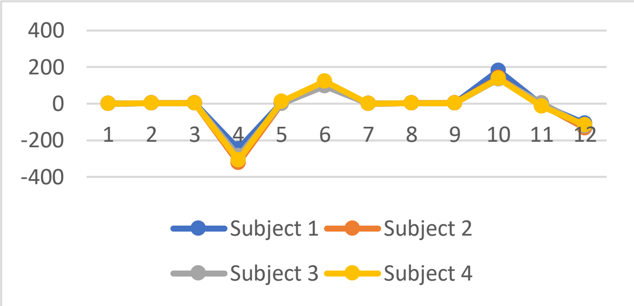
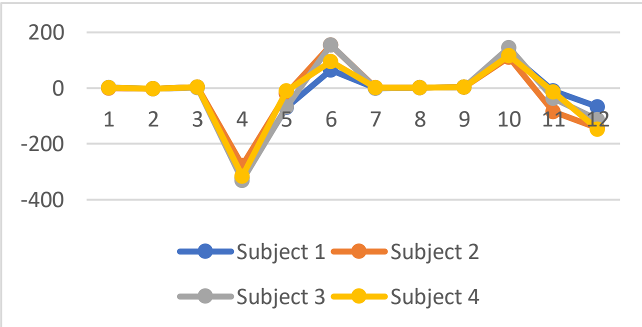
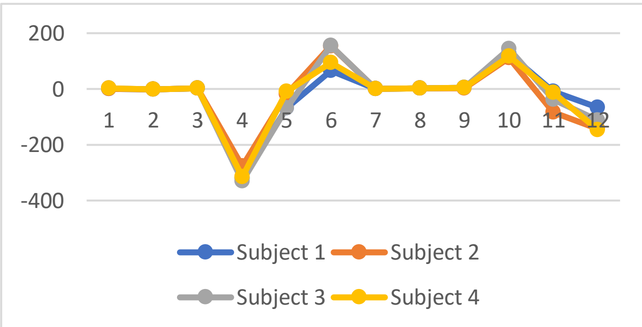
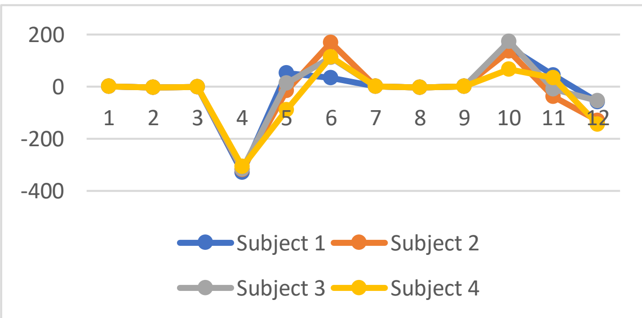
Table 2 shows the correlation coefficient of the seven exercises that were performed by the four subjects. It is clearly shown that there is a strong positive correlation between the exercises, indicating that subjects performed the exercises in a similar pattern and no outliers were discovered. Secondly, four evaluation metrics are currently being used to compare the performance of machine and deep learning algorithms, these metrics are accuracy, precision, recall and F1-score [28]. Accuracy represents the ratio of the correct prediction to the total observations, while precision represents the ratio of true positive predictions to the total positive observations. Moreover, recall or sensitivity is defined as the ratio of true positive predictions to the total observations. Finally, F1-score represents the mean of precision and recall multiplied by 2 as shown in the following mathematical equation [28].

$$F1 - score = \frac{2*Precision*Recall}{Precision*Recall} \quad \ldots\ldots.. (1)$$

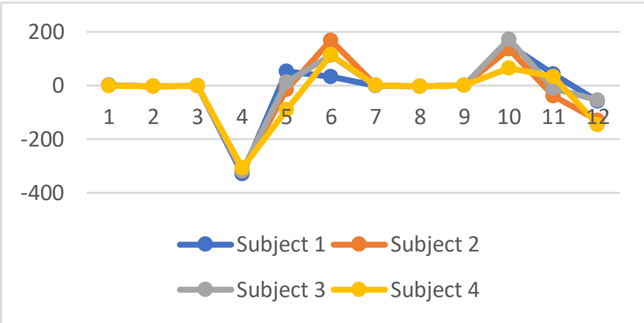
Consequently, the four metrics for the algorithms were calculated as shown in Table.3.

CNN showed highest accuracy in classifying the ACL exercises on both on real accelerometer and gyroscope data, while the Decision Tree exhibit the lowest accuracy. Random Forest came in the second place with an accuracy of around 94% which rises the potential of using this algorithm for ACL exercises classification.

Table 2: The correlation coefficient of the seven exercises performed by four subjects.

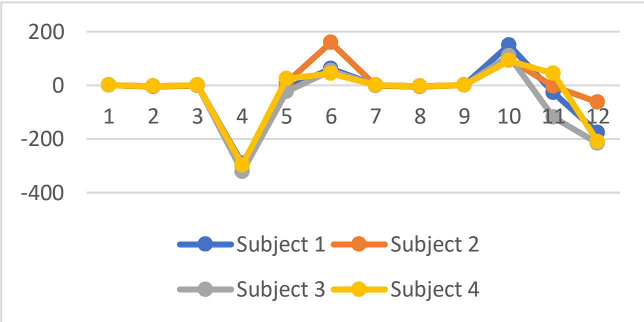
<table>
<tr><th>Label</th><th>Correlation Graph</th><th>Correlation Matrix</th></tr>
<tr><td>First Exercise</td><td>
</td><td>
<table>
<tr><td>Corr.</td><td>S1</td><td>S2</td><td>S3</td><td>S4</td></tr>
<tr><td>S1</td><td>1</td><td>0.984</td><td>0.986</td><td>0.983</td></tr>
<tr><td>S2</td><td>0.984</td><td>1</td><td>0.999</td><td>0.998</td></tr>
<tr><td>S3</td><td>0.986</td><td>0.999</td><td>1</td><td>0.996</td></tr>
<tr><td>S4</td><td>0.983</td><td>0.998</td><td>0.996</td><td>1</td></tr>
</table></td></tr>
<tr><td>Second Exercise</td><td>
</td><td>
<table>
<tr><td>Corr.</td><td>S1</td><td>S2</td><td>S3</td><td>S4</td></tr>
<tr><td>S1</td><td>1</td><td>0.910</td><td>0.971</td><td>0.960</td></tr>
<tr><td>S2</td><td>0.910</td><td>1</td><td>0.974</td><td>0.96</td></tr>
<tr><td>S3</td><td>0.971</td><td>0.974</td><td>1</td><td>0.972</td></tr>
<tr><td>S4</td><td>0.960</td><td>0.963</td><td>0.972</td><td>1</td></tr>
</table></td></tr>
<tr><td>Third Exercise</td><td>
</td><td>
<table>
<tr><td>Corr.</td><td>S1</td><td>S2</td><td>S3</td><td>S4</td></tr>
<tr><td>S1</td><td>1</td><td>0.948</td><td>0.927</td><td>0.907</td></tr>
<tr><td>S2</td><td>0.948</td><td>1</td><td>0.957</td><td>0.908</td></tr>
<tr><td>S3</td><td>0.927</td><td>0.957</td><td>1</td><td>0.845</td></tr>
<tr><td>S4</td><td>0.907</td><td>0.908</td><td>0.845</td><td>1</td></tr>
</table></td></tr>
<tr><td>Fourth Exercise</td><td>
</td><td>
<table>
<tr><td>Corr.</td><td>S1</td><td>S2</td><td>S3</td><td>S4</td></tr>
<tr><td>S1</td><td>1</td><td>0.890</td><td>0.961</td><td>0.861</td></tr>
<tr><td>S2</td><td>0.890</td><td>1</td><td>0.967</td><td>0.946</td></tr>
<tr><td>S3</td><td>0.961</td><td>0.967</td><td>1</td><td>0.902</td></tr>
<tr><td>S4</td><td>0.861</td><td>0.946</td><td>0.902</td><td>1</td></tr>
</table></td></tr>
</table>

Fifth Exercise



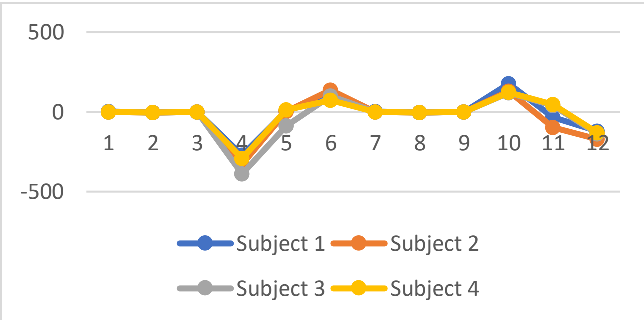
Corr.	S1	S2	S3	S4
S1	1	0.990	0.676	0.937
S2	0.990	1	0.676	0.927
S3	0.676	0.676	1	0.847
S4	0.937	0.927	0.847	1

Sixth Exercise



Corr.	S1	S2	S3	S4
S1	1	0.914	0.973	0.959
S2	0.914	1	0.882	0.873
S3	0.973	0.882	1	0.914
S4	0.959	0.873	0.914	1

Seventh Exercise



Corr.	S1	S2	S3	S4
S1	1	0.975	0.932	0.957
S2	0.975	1	0.909	0.924
S3	0.932	0.909	1	0.969
S4	0.957	0.924	0.969	1

Table 3: The performance of the ML and DL algorithms relying on both real accelerometer and gyroscope data.

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.875	0.879	0.875	0.873
Decision Tree	0.869	0.870	0.870	0.869
Random Forest	0.939	0.939	0.939	0.938
Gradient Boosting	0.899	0.900	0.899	0.899
KNN	0.916	0.917	0.916	0.916
CNN	**0.960**	**0.950**	**0.947**	**0.948**

Recalling that each sensor provides 6 readings (3 for accelerometer and 3 for gyroscope), it was suggested to check the algorithms performance with excluding gyroscope' data. Table.4 shows the performance of the algorithms relying only on the accelerometer's data. On the contrary to previous measurements, Random Forests showed the highest accuracy. However, the performance metrics were substantially downgraded when employing the accelerometer's data only. Therefore, it is recommended to employ accelerometer and gyroscope data to train the algorithm for ACL exercises recognition.

For further clarification, fig.4 shows that the accuracy obtained across different aforementioned models. It is clear that CNN achieving heightened accuracy score with real accelerometer and gyroscope readings in our dataset followed by Random Forests.

Table 4: The performance of the ML and DL algorithms relying on real accelerometer data only.

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.796	0.800	0.796	0.791
Decision Tree	0.827	0.827	0.828	0.828
Random Forest	**0.883**	**0.884**	**0.883**	**0.884**
Gradient Boosting	0.850	0.850	0.850	0.849
KNN	0.861	0.861	0.861	0.860
CNN	0.809	0.787	0.780	0.780

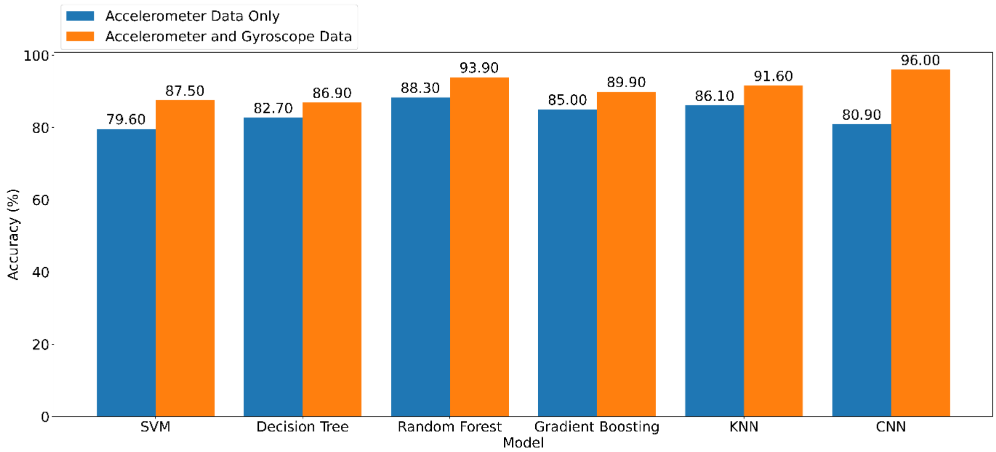


Figure 4: Comparison of the accuracy across different models with two scenarios using only accelerometer data (blue bars), and both accelerometer and gyroscope data (orange bars).

In respect to data augmentation, the performance of the classification models improved slightly after generating new samples and combining them with the real data, as shown in Tables 5, 6, 7, and 8. Two augmentation ratios—50% and 100% of the original dataset—were utilized to evaluate their impact on accuracy. Table 5 and 7 showed that Random Forest and CNN exhibited the highest and similar accuracy when new data employed relying on accelerometer and gyroscope data. Moreover, table 6 and 8 proved that using only accelerometer data has downgraded the models' accuracy. Figures 5 and 6 compare between the models employing 50% and 100% augmented data. To conclude, both CNN and Random Forest models performed well for classification purposes and achieved higher accuracy among the other algorithms with real accelerometer and gyroscope data. However Random Forest model outperformed CNN model when applied on real accelerometer data only or with synthesized data.

Table 5: The performance of the ML and DL algorithms relying on both real accelerometer and gyroscope data combining with 50% of synthesized data.

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.875	0.877	0.875	0.874
Decision Tree	0.910	0.909	0.909	0.909
Random Forest	**0.959**	**0.959**	**0.959**	**0.958**
Gradient Boosting	0.922	0.922	0.922	0.922
KNN	0.879	0.879	0.879	0.878
CNN	0.951	0.944	0.942	0.942

Table 6: The performance of the ML and DL algorithms relying only on real accelerometer data only combining with 50% of synthesized data.

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.816	0.817	0.815	0.815
Decision Tree	0.877	0.877	0.878	0.876
Random Forest	**0.920**	**0.920**	**0.919**	**0.919**
Gradient Boosting	0.887	0.887	0.887	0.886
KNN	0.872	0.872	0.871	0.871
CNN	0.805	0.797	0.786	0.787

Table 7: The performance of the ML and DL algorithms relying on both real accelerometer and gyroscope data combining with 100% of synthesized data.

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.904	0.906	0.904	0.904
Decision Tree	0.929	0.929	0.929	0.929
Random Forest	**0.969**	**0.969**	**0.969**	**0.969**
Gradient Boosting	0.937	0.937	0.937	0.937
KNN	0.908	0.908	0.908	0.908
CNN	0.958	0.953	0.952	0.953

Table 8: The performance of the ML and DL algorithms relying only on real accelerometer data only combining with 100% of synthesized data.

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.857	0.858	0.857	0.857
Decision Tree	0.905	0.905	0.904	0.905
Random Forest	**0.939**	**0.939**	**0.939**	**0.939**
Gradient Boosting	0.909	0.909	0.909	0.909
KNN	0.901	0.900	0.901	0.900
CNN	0.830	0.828	0.819	0.821

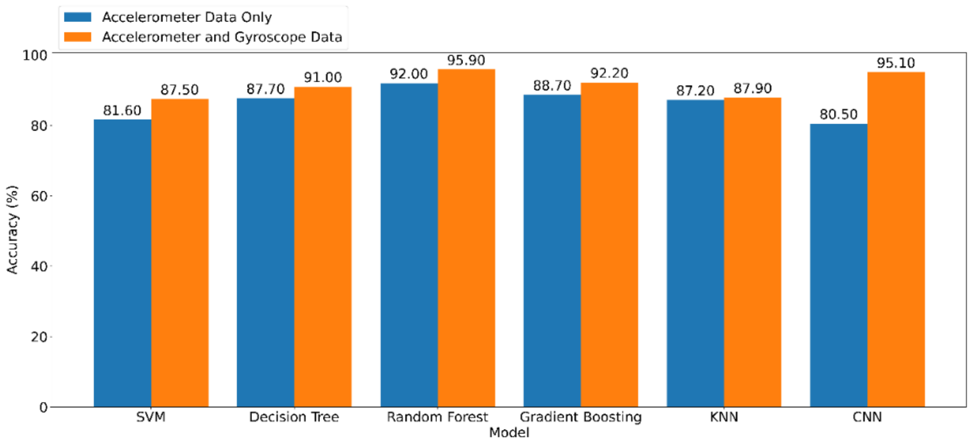


Figure 5: Comparison of the accuracy across different models with two scenarios using only accelerometer data (blue bars), and both accelerometer and gyroscope data (orange bars) combining with 50% of synthesized data.

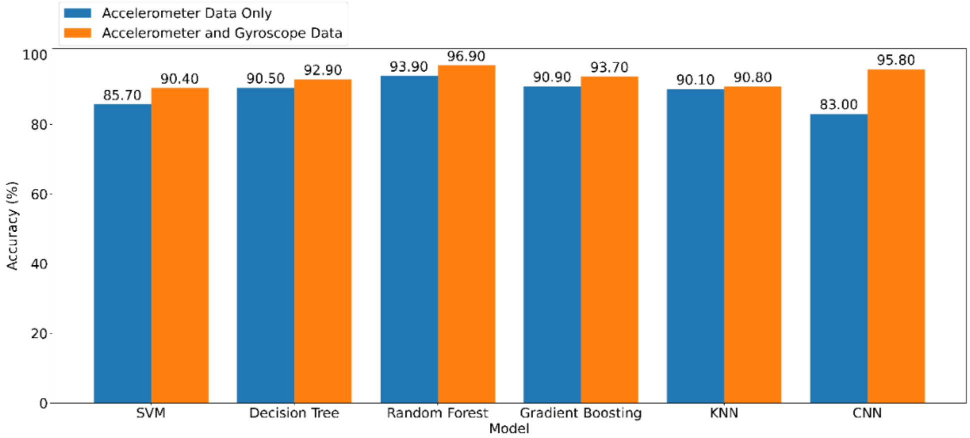


Figure 6: Comparison of the accuracy across different models with two scenarios using only accelerometer data (blue bars), and both accelerometer and gyroscope data (orange bars) combining with 100% of synthesized data.

Lastly, this study faced two main limitations, firstly related to the limited number of training samples that could dramatically affect the performance of ML and DL models. Despite the fact that data augmentation was applied to overcome this issue, employing more participants in the study provides realistic data which enhances the training process in terms of model's generalization. Secondly, the exercises variation that were considered in this study and their employed data. Adding more ACL exercises to the study would positively impact the model's performance and improve the exercises recognition accuracy.

Conclusion and Future works

Five ML algorithms, SVM, Decision Tree, Random Forest, Gradient boosting and KNN, with CNN were used to classify seven ACL exercises performed by four subjects. The datasets, that were used to train the algorithms, were extracted from accelerometer and gyroscope sensors attached to the thigh and shank. Moreover, new data were synthesized using different techniques to overcome the insufficient data issue. Results showed that CNN and Random Forest achieved higher accuracy among the employed algorithms with real accelerometer and gyroscope data, followed by the KNN with an accuracy over 90%. However, Random Forest model outperformed other models when relying on real accelerometer data only or with synthesized data. This could be very useful when utilizing this system for real time application especially after applying data augmentation in order to decrease the computational resources. It was also found that gyroscope data were essential to train the algorithms efficiently and excluding such data leads to downgrade the classification performance.

Future works could involve positioning multiple sensors that can be used to recognize human activities and recording various physiological measurements simultaneously. Such endeavor inspects the relationship between human activities and other physiological parameters. Moreover, increasing the number of the participants could reveal potential abilities of the employed algorithms and consider the algorithms' real-time response in complex setting.

Abbreviations

ACL	Anterior Cruciate Ligament
GPS	Global Positioning System
AI	Artificial Intelligence
ML	Machine Learning
SVM	Support Vector Machine
KNN	K-nearest Neighbors
DL	Deep Learning
CNN	Convolutional Neural Network
IMUs	Inertial Measurement Units
IDE	Integrated Development Environment
CSV	Comma-separated values

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