Egyptian Informatics Journal 27 (2024) 100534

Contents lists available at ScienceDirect

Egyptian Informatics Journal

journal homepage: www.sciencedirect.com

Full Length Article

Classification and monitoring of arm exercises using machine learning and wrist-worn band

Aamer Bilal Asghar [a], Maham Majeed [a], Abdullah Taseer [a], Muhammad Burhan Khan [a], Khazina Naveed [b], Mujtaba Hussain Jaffery [a], Ahmed Sayed Mohammed Metwally [c], Krzysztof Ejsmont [d,*], Mirosław Nejman [d]

[a] Department of Electrical and Computer Engineering, COMSATS University Islamabad, Lahore 54000, Pakistan
[b] Department of Computer Science, Bahria University, Lahore 54000, Pakistan
[c] Department of Mathematics, College of Science, King Saud University, Riyadh 11451, Saudi Arabia
[d] Faculty of Mechanical and Industrial Engineering, Warsaw University of Technology, 02-524 Warsaw, Poland

ARTICLE INFO

Keywords:
KNN
SVM
Boosted Trees
Classification
IoT
Sensors

ABSTRACT

Exercise is essential for a healthy lifestyle, thus it is important to consider how to keep proper posture when performing arm exercises at home. This work uses wrist-worn bands with the MPU6050 sensor to address these issues, which collects motion data using acceleration measurements. The individuals in the dataset are completing a variety of activities at varying ranges of motion. Machine learning-based classification methods are then applied after the pre-processing and feature extraction of the gathered data. An App prototype integrated with a WiFi module and Cloud infrastructure is created to enable real-time data collecting and storage. The Arduino IDE is used to send the collected data to the ThingSpeak platform, where it is subsequently sent to MATLAB for additional analysis. The studied data is then returned to ThingSpeak, where the program displays the findings. This approach reduces the risk of injuries caused by bad posture by enabling people to continue regular workouts at home without requiring a personal trainer or a particular environment. The findings of this work shed important light on the performance of Boosted Trees, Quadratic SVM, Subspace KNN, and Fine KNN algorithms for arm exercises employing a wrist-worn band with an MPU6050 sensor. The Fine KNN has the highest accuracy of 91.3% among all implemented algorithms.

1. Introduction

Wearable sensors monitor physiological signs along with other symptoms such as breathing, pulse, walking pattern, etc. to detect unusual or unexpected events and help can accordingly be provided if needed [1]. The MPU-6050 is worn on the wrist to collect information from the user's arm movements. The data is sent to a microcontroller and the amount of movement is measured through an accelerometer. The actual output of the MPU-6050 is compared with pre-set values via a microcontroller and suppressed by a classification algorithm. This causes muscle contraction and inhibits movement. This operation continues in a loop to ensure a stable body. Using Android and cloud applications, users can view the statistics generated by the sensors and send signals to the accelerometer to prevent movement. The cuff can also be used as a fashion item and the color can be customized according to the patient's preference, making it tempting to wear [2–4].

Recent years have seen significant developments in the field of wearable technology in healthcare, with a focus on applications involving artificial intelligence and machine learning. Because they can monitor vital signs and track human activity, these wearables have potential use in patient monitoring, medical diagnostics, and elder care. Critical obstacles still exist despite developments, such as the requirement for accurate sensor data interpretation, which affects the efficacy and dependability of arm exercise monitoring systems in both home and healthcare environments. Despite the rise of smartwatches and other wearables, researchers have highlighted the need to remove current obstacles and suggest directions for further investigation and development [5].

The major contributions of this research work are given below,

* Corresponding author.
E-mail address: krzysztof.ejsmont@pw.edu.pl (K. Ejsmont).

https://doi.org/10.1016/j.eij.2024.100534
Received 16 October 2023; Received in revised form 8 July 2024; Accepted 28 August 2024
Available online 7 September 2024

i. This study involves the simulations and hardware development involving electronic sensors, controllers, interfaces, and App development.
ii. Real-time data is collected from the electronic sensors and is used for classification by machine learning algorithms. Subspace K-nearest neighbor (KNN), fine KNN, boosted trees, and quadratic support vector machines (SVM) are used for comprehending this complex data.
iii. The simulation results have been experimentally validated on the developed hardware setup.
iv. A dedicated mobile application has been developed as an interface medium between the machine and the user.
v. By comparing selected algorithms, this study offers insight into their suitability and effectiveness for arm exercise monitoring.
vi. The developed hardware setup and implemented machine learning algorithms can help citizens to maintain proper posture during arm exercises as poor posture can result in long-term back pain and tendonitis.

To conduct this study, participants have been asked to perform various arm exercises with wristbands, and data is collected from these exercises. After a comprehensive pre-processing stage to remove noise and unnecessary information, the gathered data is split into training and test sets for the machine learning algorithms that are being examined. An ensemble learning technique called Boosted Trees combines weak learners, usually decision trees, to create a robust learner. A modification of the classical KNN technique called Subspace KNN uses a subset of features for each query point, which is useful when working with high-dimensional data. Another KNN variation called Fine KNN uses a weighted distance metric to rank closest neighbors, which improves performance in cases where the dataset has different densities.

This paper is organized as, section 2 (literature review) provides a detailed analysis of previous studies that have investigated a range of technologies, such as accelerometers, Inertial Measurement Units (IMUs), and smart wearables to improve the accuracy and accessibility for tracking arm movements. Section 3 explains the overall methodology that has been used in this study for data collection, software and hardware development, and its implementation. The results and discussions are presented in section 4. Section 5 summarizes the conclusion and the future work.

2. Literature review

Several studies have investigated the use of sensor wristbands to monitor various physical activities, including arm movements. The authors in ref [6] investigated the possibility of using a wrist-worn accelerometer to accurately track and classify arm movements during a routine exercise. Another study at ref [7] presents the concept of using wristband data in the automated delivery of insulin.

Machine learning algorithms are increasingly used to analyze training data and provide valuable insights. A study investigated the effectiveness of KNN in classifying movement types based on accelerometer data from wearable devices [8]. The researchers in ref [9] reported promising results in the accurate detection of different arm exercises, which paved the way for further exploration. Similarly, in ref [10] the performance of several machine learning techniques including boosted trees and Fine KNN is compared in analyzing motion patterns from wearable sensors. The results emphasized how important it is to choose an appropriate methodology for accurate motor assessment.

Although studies have explored the use of machine learning algorithms in motion assessment, few studies have specifically focused on arm motions using wristbands to determine whether a machine learning algorithm using a three-axis accelerometer, gyroscope, and magnetometer data from an Inertial Motion Unit (IMU) can detect surface and age differences in gait [11]. The authors in ref [12] conducted a preliminary study in which participants performed a series of predefined arm exercises while wearing a wrist brace, and the data were processed using KNN. Even though the results show promise for precise motion classification, this study emphasizes the need for more research using different methods.

The effectiveness of machine learning algorithms in exercise monitoring strongly depends on the selection of evaluation criteria. The importance of metrics such as accuracy, precision, recall, and F1 score in evaluating the performance of classification models for a motion detection task. The researchers emphasized the importance of considering all these criteria to comprehensively understand the effectiveness of the algorithms [13]. Another study investigated the effects of scapular movement on neck and muscle alignment in patients with forward head postures whose structural changes around the neck have been caused by forward head postures when scapular stabilization exercises are applied [14].

Myoware sensors had been utilized to track the motion of the shoulders and arms of hemiplegic individuals in a separate investigation. EMG data was collected from three muscles as shown in Fig. 1. It was shown that the sensors could pick up on minute variations in muscle activation patterns brought on by alterations in training intensity. Consider carrying a Myoware tracking device with sensors and machine learning on the next arm workout [15–18]. Another study demonstrates the system's ability to appropriately categorize a variety of arm exercises and provide real-time feedback on muscle activation [19].

Anticipating the time of an impending pandemic reduces the impact of disease by taking preventive steps such as sending public health messages and raising awareness among physicians [20]. With the continuous and rapid increase in the cumulative incidence of COVID-19, the research community is using statistical and outbreak prediction models, including various machine learning (ML) models, to track and predict the trend of the epidemic, as well as to develop appropriate strategies to combat and control its spread [21–24].

Another study establishes cut-off values for GENEActiv (accelerometer) intensity in older adults and compares classification accuracy between dominant (D) and non-dominant (ND) wrists, using both laboratory and wildlife data [12,25]. A comprehensive survey and classification of smart wearables and research prototypes using machine learning and AI technologies have been presented in different studies [26]. An overview of various areas of machine learning for medical wearables is presented in ref [27] to provide adaptive extreme edge computing.

Algorithms that can determine physical activity (PA) type and quantify intensity may enable precision medicine approaches such as automated insulin delivery systems that modulate insulin delivery in response to PA [28]. Deep learning networks using bidirectional long-short-term memory networks were trained on sensor data

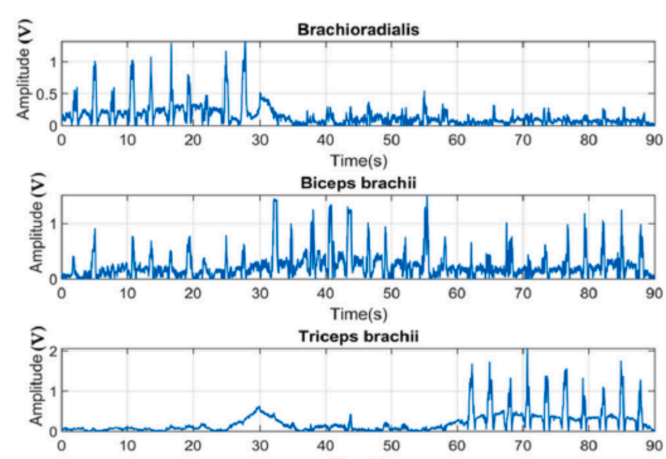

Fig. 1. Electromyography (EMG) data collected from 3 muscles [12].

(acceleration, gyroscope signals, and EMG) using video-annotated activities as targets [29]. A very promising device in the framework of sitting position monitoring, as it is non-invasive and can be conveniently placed on a seat or backrest, making an ordinary chair, wheelchair, sofa, or even a car seat suddenly smart [30].

With the growing popularity of wearables for both recreational and health initiatives, understanding the strengths and limitations of these technologies is increasingly important [31]. Fig. 2 shows wearable components which are connected to the device. There is a need for continuous evaluation of the effectiveness of wearable devices to accurately and reliably measure claimed outcomes [32]. In ref [33] authors used a mixed methods design (concurrent triangulation). Thus, both qualitative and quantitative data were collected during the study and the final interpretation relied on the integration of the findings.

The author uses an accelerometer-equipped machine learning system with six curve-fitting-based models to fully identify the state of upper limb rehabilitation exercise completion. Using machine learning techniques to differentiate between useful and non-functional movements, it presents the ARM device, which consists of a single IMU on the wrist. Especially, the study demonstrates how reliable the Random Forests (RF) and Convolutional Neural Networks (CNN) classifiers are in tracking arm motion. The goal was to highlight how human intelligence and experience are integrated with the features of a home-based rehabilitation system that includes arm guards and a smart glove. The device, which is portable and has a flexible sensor, is designed to track arm movement continually and address problems with complexity and size [34].

3. Methodology

The overall methodology of using the data of wrist-worn bands and machine learning algorithms for arm exercise monitoring is given in Fig. 3.

3.1. Hardware

The wristband includes MPU-6050 digital accelerometer and gyroscope, NODEMCU ESP8266, OLED, MAX30102 pressure sensor, and Li-ion battery as power supply. The MPU-6050 sensor records the acceleration changes that occur during exercise, the NODEMCU processes and stores these acceleration data and sends them to the cloud. An Android mobile application shows whether an exercise is correct or incorrect. 0.96-inch OLED displays the current time and temperature. A pressure sensor is used to measure blood flow. Fig. 4 shows the hardware components.

Data collection during arm workouts was done with careful

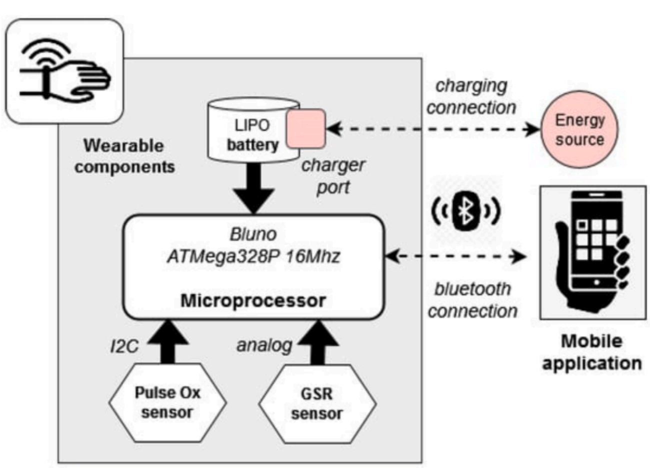

Fig. 2. HealthCare Wearable Device [29].

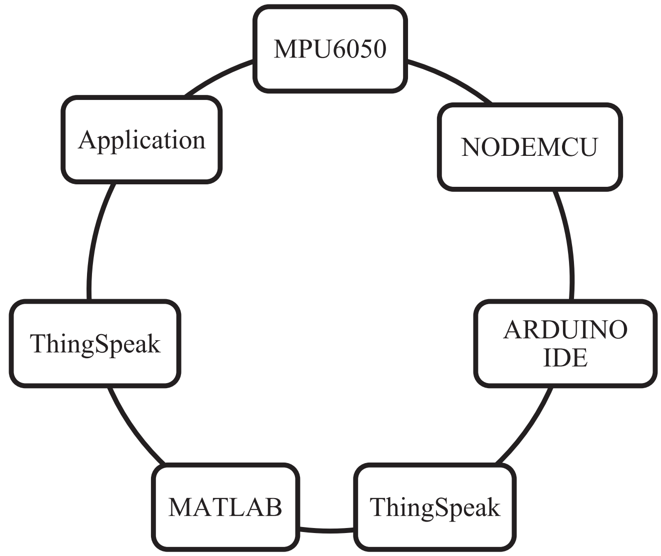

Fig. 3. Flow Diagram.

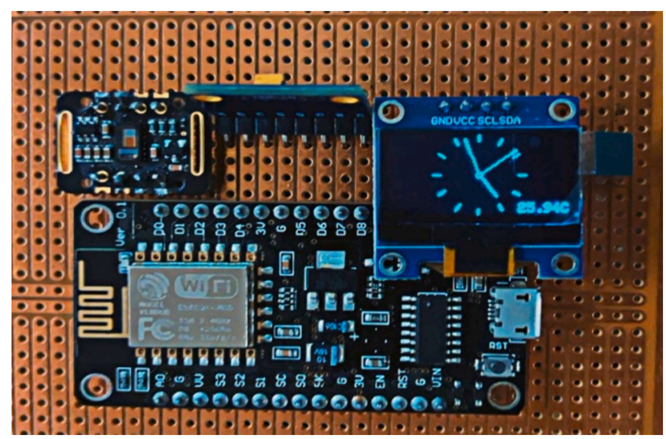

Fig. 4. Hardware Components.

consideration, with an emphasis on relevance and comprehensiveness. A collection of biceps, triceps, and hammer curls were among the targeted arm workouts that ten individuals actively performed. The workouts that were selected were particularly created to include a range of upper limb motions, providing a representative dataset for efficient analysis. The controlled atmosphere in which the data gathering was conducted ensured consistency and reduced the impact of outside factors. Because of this controlled environment, researchers were able to carefully watch and document the motions of participants during each exercise, ensuring that high-quality data would be collected for further analysis and assessment.

3.2. Software

The software section shows how raw sensor data is processed with careful consideration. Robust preparation methods were employed to fix up and get the data ready for analysis. Furthermore, the dataset was further improved by the application of advanced feature extraction techniques, which allowed for a deeper understanding and increased the study's overall efficacy. The first step involves a data set that contains 4 columns, three inputs, and one output. The data included accelerometer readings from the MPU-6050 sensor. The output is in the form of binary code, which is a correct and incorrect form. Several machine learning algorithms were then selected in MATLAB for analysis. These algorithms include Boosted Trees, Quadratic SVM, Subspace KNN, and Fine KNN. The selected machine learning algorithms were then trained using the extracted features as input and the corresponding training labels as output. Model training was done using a portion of the collected data known as the training set. The trained machine learning models were then evaluated using a separate part of the collected data, the test set. The performance of each algorithm is evaluated based on several metrics such as accuracy, precision, recall, and F1 score [6,7]. Finally, a comparative analysis was performed to determine the most efficient algorithm for arm exercise classification using wrist-worn band.

$$Precision = \frac{TruePositives}{ActualResults} or \frac{TruePositives}{TruePositives + FalsePositives} \tag{1}$$

$$Recall = \frac{TruePositives}{PredictedResults} or \frac{TruePositives}{TruePositives + FalseNegatives} \tag{2}$$

$$Accuracy = \frac{TruePositives + TrueNegatives}{TruePositives + TrueNegatives + FalsePositives + FalseNegatives} \tag{3}$$

$$F1\ score = \frac{2 \times Precision \times \mathrm{Recall}}{Precision + \mathrm{Recall}} \tag{4}$$

The Arduino IDE configures the NODEMCU ESP8266 and places the program input to each sensor node. It includes many code editor features such as brace matching, syntax highlighting, and automatic indentation. Data is sent to ThingSpeak using the Arduino IDE, and from ThingSpeak, data is sent to MATLAB and sent to ThingSpeak. Prediction can also be done in real time using MATLAB R2020. Fig. 5 shows the Ax accelerometer readings with the date. ThingSpeak shows the accelerometer readings as shown in Figs. 6 and 7. MATLAB can predict in the form of binary 0 and 1. Where 0 indicates wrong 1 indicates correct and the output shows the application.

Machine learning algorithms have few pros and cons associated with them based on their structure. Artificial Neural Networks (ANNs) are black box in nature and do not interpret what is actually happening inside the black box. ANNs require large dataset of labeled samples than traditional machine learning algorithms. ANNs can be computationally expensive and deep learning algorithms may take weeks for training and require high power computational units such as Graphics processing unit (GPU). Bayesian networks are based on probabilistic theory but designing the Bayesian network may require a lot of efforts as there is no universally accepted method for constructing the network from data. Therefore, building and maintaining a complex Bayesian model with many variables can be time consuming. Moreover, learning with less, missing or incomplete data can be challenging and it can negatively affect the performance of the Bayesian network. Bayesian networks cannot represent cyclic (feedback loop) dependencies between variables

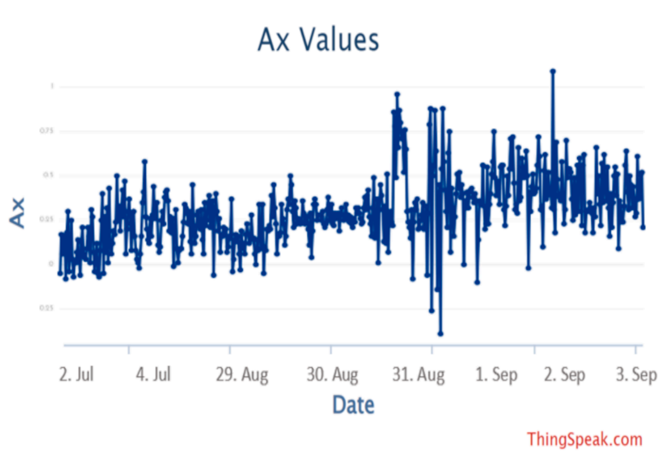

Fig. 5. ThingSpeak showing Ax Data.

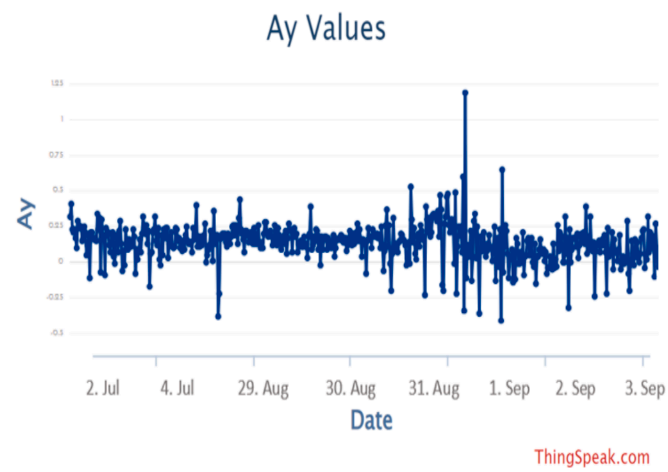

Fig. 6. ThingSpeak showing Ay Data.

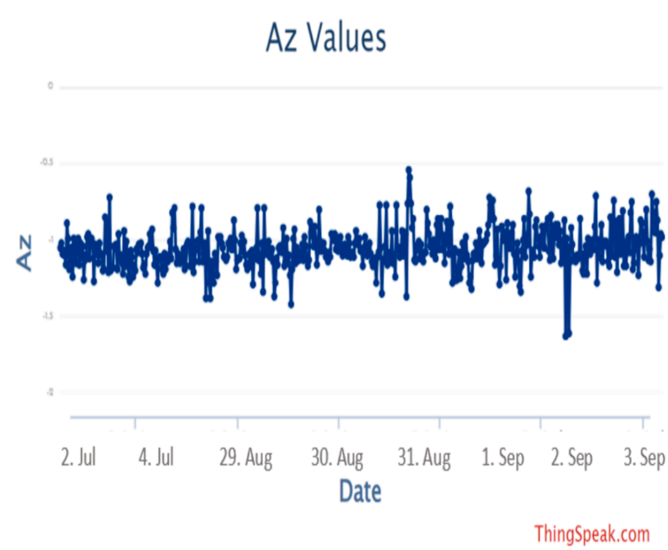

Fig. 7. ThingSpeak showing Az Data.

which limit their applicability of certain problems. Logistic regression is also a well-known classification algorithm which requires large data size for reliable results. The major limitation associated with logistic regression is the assumption of linearity between dependent and independent variables. Logistic regression cannot solve nonlinear problems due to its linear decision surface. XGBoost and LightGBM algorithms are based on gradient boosted machines. In XGBoost algorithm the tree grows depth wise while in LightGBM the tree grows leaf-wise. The performance of XGBoost algorithm is compromised in terms of loss function and scalability. XGBoost is a time consuming algorithm and can be computationally inefficient for processing large data set with complex structures having many hyper parameters. In contrast LightGBM is a fast algorithm with reduced run time and less computational cost. LightGBM is good to handle large data but it has certain randomness in the parameters selection making it difficult to determine the optimal combination of parameters. Moreover, LightGBM is prone to overfitting for small data and complex trees.

The selected machine learning algorithms Boosted Trees, Quadratic SVM, Subspace KNN, and Fine KNN showcase a strong collection that provides a comprehensive method for pattern recognition and classification applications. Boosted Trees combines weak learners to achieve high accuracy in ensemble learning. In challenging datasets, quadratic SVM is skilled in managing non-linear relationships and obtaining the best separation. Subspace KNN and Fine KNN add adaptability and flexibility by supporting different data structures and enabling minor distinctions. Their combined strength is their flexibility in responding to various characteristics seen in sensor data, demonstrating a thorough approach to efficient workout completion status recognition. Investigating deep learning techniques may improve the system's capacity to manage complex data patterns, promoting future adaptability and scalability for changing therapy needs.

3.3. App development

The first step to this is to design a user interface that is easy to use and visually appealing. The welcome page should include sign-up and login buttons. After logging in, users should be taken to the home screen. Choose what you want to do. After selecting it, move to the next screen. Then select the Start button. Then the band runs a prediction and shows if the person is doing the exercise correctly or not. Fig. 8 shows the front page of the Fitness First App,

4. Results and discussion

The hardware used for testing is shown in Fig. 9. The precision, recall, F1-score, and accuracy of the implemented machine-learning algorithms (boosted tree, quadratic SVM, subspace KNN and fine KNN) have been shown in Table 1. The machine-learning algorithms were selected with consideration to ensure that they would work well for assessing arm exercises that were done with wrist-worn bands. Exercise movement patterns can be identified by Fine KNN (K-Nearest Neighbours), which is well-known for its efficiency in handling classification problems by taking data point proximity into account.

Fig. 10 shows the values of the accelerometer which are Ax, Ay, and Az. Real-time prediction of the exercise using the band is shown in Fig. 11. Here, 1 means it is correct.

Fig. 12 shows the output of the prediction on the application which is corrected.

For assessing arm exercises utilizing a wrist-worn band, Boosted Trees, Quadratic SVM, Subspace KNN, and Fine KNN algorithms were compared, and the results were noteworthy. The accuracy of the Fine KNN algorithm was 91.3 % which is shown in Fig. 13, and that of the other techniques was less than the above. KNN is prioritized because of its fundamental advantages, which make it a useful option for a range of applications. It has a reputation for being easy to use, and adaptable to positions involving both regression and classification. Because it is non-parametric, it may adjust to various data distributions without assuming any particular underlying patterns, which makes it very helpful for dynamic and varied datasets. Furthermore, KNN does exceptionally well at identifying local links within the data, demonstrating its usefulness in situations where proximity-based information is essential. The algorithm's importance and significance in machine learning applications are highlighted by its versatility and ease of use across several domains. The confusion matrix of the subspace KNN is shown in Fig. 14. These findings demonstrate the efficiency of the four above algorithms in categorizing and analyzing workout movements, with the accuracy of the Fine KNN approach significantly better.

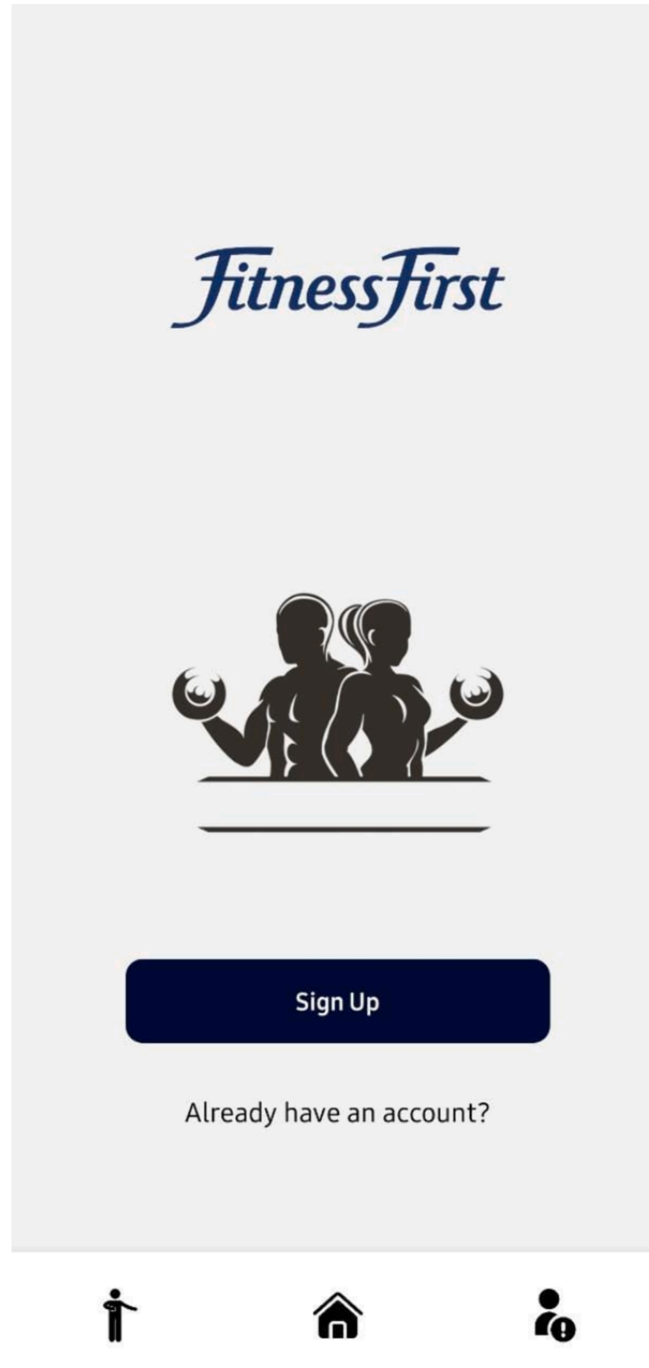

Fig. 8. The Fitness App.

4.1. ROC curve

An effective method for assessing the effectiveness of classification algorithms is the ROC (Receiver Operating Characteristic) curve. It sheds light on how the genuine positive rate and the false positive rate compare at different classification levels. It may evaluate the discriminative power and selectivity of the algorithms in identifying arm exercise patterns by drawing the ROC curve for each approach.

The Fine KNN algorithm's ROC curve shown in Fig. 15 has a sharp early ascent, signifying a high true positive rate at a low false positive rate. This shows that the algorithm accurately classifies distinct workout actions by efficiently differentiating between them. The ROC curve for the Subspace KNN method, on the other hand, shows a more gradual climb, indicating a substantially lower true positive rate at comparable false positive rates. The performance of the Subspace KNN approach is good and its accuracy is 89 % as shown in Fig. 16; however, it might be a little less sensitive than the Fine KNN algorithm.

4.2. Scatter plot

An illustration that clarifies the distribution and grouping of data points is a scatter plot. By evaluating the outcomes on a scatter plot, one can obtain a greater understanding of how well these algorithms distinguish between different arm exercise processes.

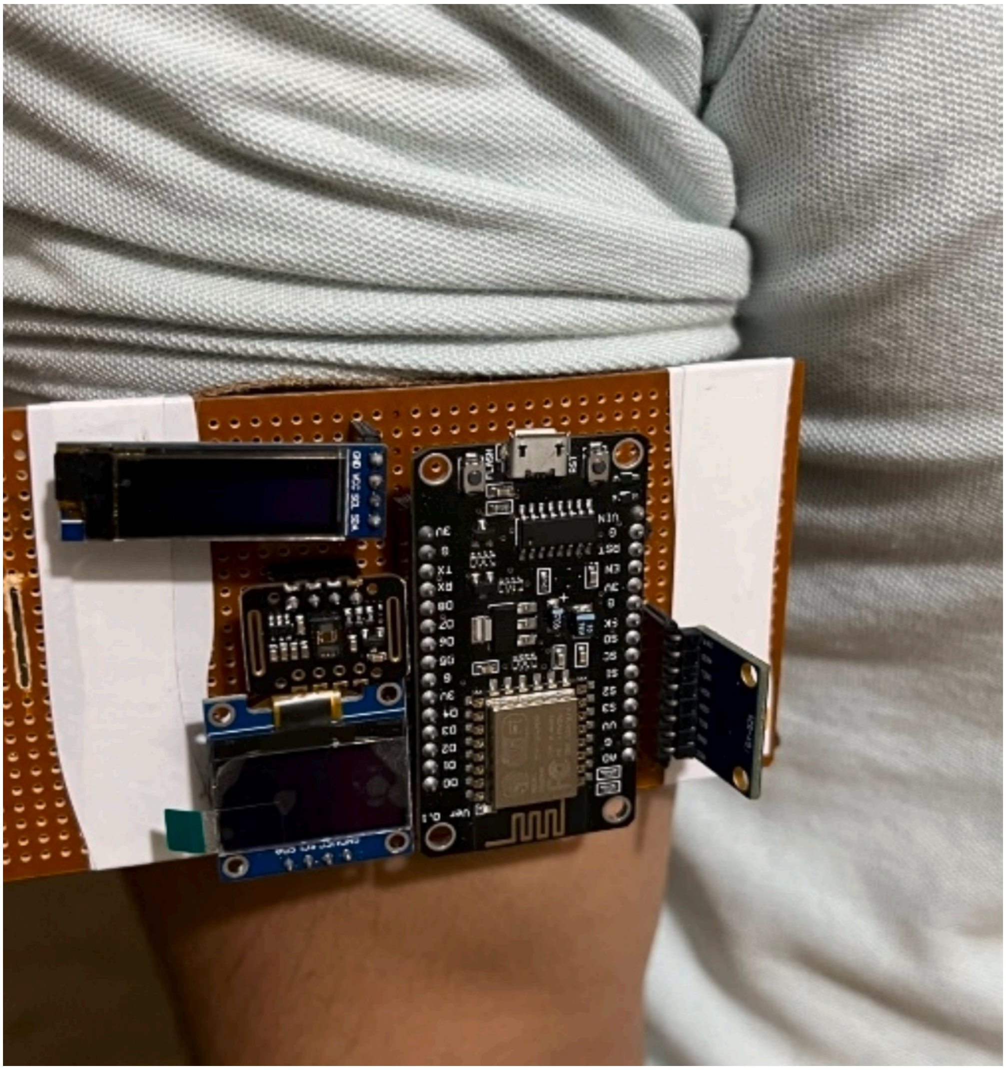

Fig. 9. Hardware Testing.

Table 1
Accuracy of Algorithms.

Algorithm Name	Precision	Recall	F1Score	Accuracy %
Fine KNN	0.90	0.92	0.90	91.3
Quadratic SVM	0.94	0.81	0.87	85.2
Boosted Trees	0.94	0.81	0.87	85.5
Subspace KNN	0.91	0.88	0.89	89.0

The Fine KNN method's scatter plot displays discrete clusters of data points, demonstrating that the algorithm successfully combines comparable exercise patterns in Fig. 18. The algorithm appears to be successful in capturing the underlying patterns and variances in arm exercises, according to this clustering. Similar to this, the scatter plot for the other algorithms exhibits reasonably well-defined clusters, despite some overlap between various exercise patterns. As opposed to the Fine KNN method, this suggests that the algorithm is also capable of differentiating between distinct workout movements, but with a slightly lower level of separation. Fig. 17 shows the scatter plot of the Subspace KNN.

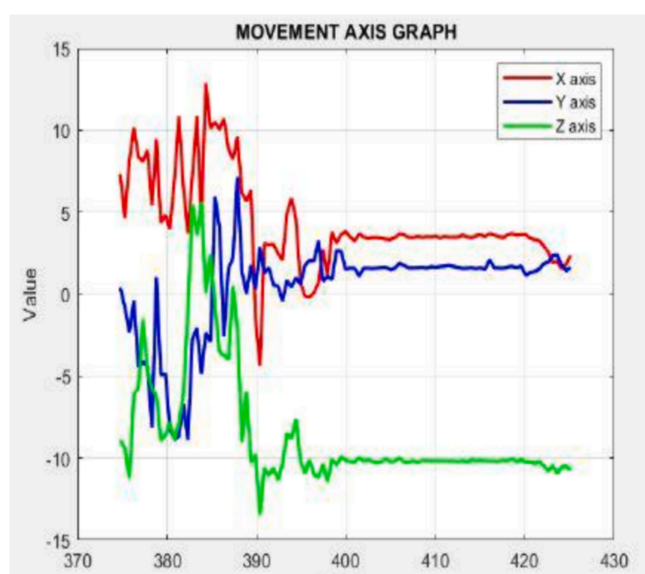

Fig. 10. Graph showing the accelerometer axis on MATLAB.

4.3. Curve of parallel coordinates

Visualizing parallel coordinates is an effective method for comparing

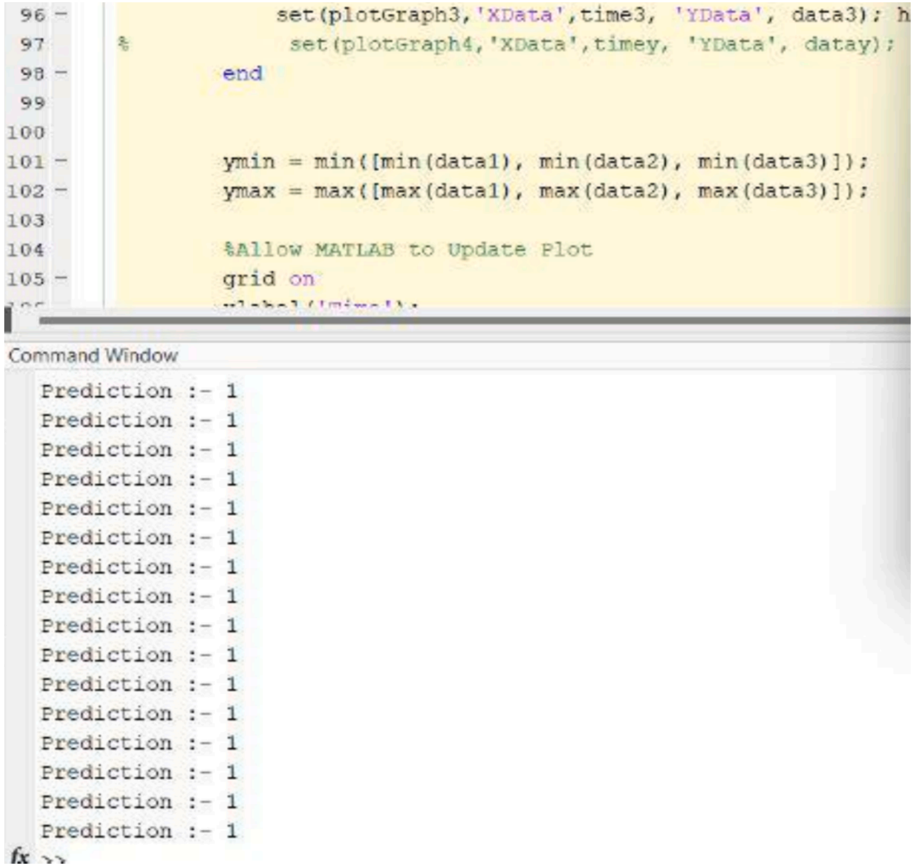

Fig. 11. Correct Form of Prediction on MATLAB.

several variables at once. Plotting results of the Fine KNN algorithm on parallel coordinate curves allows one to observe the behavior and correlations of different features in the classification of arm workouts, as shown in Fig. 19.

For each workout movement along the parallel axes, the parallel coordinates curve for the Fine KNN algorithm reveals distinct and distinct patterns. This shows that the algorithm successfully distinguishes between various arm activities using the features retrieved from the wrist-worn band data. On the other hand, despite having some overlapped sections, the parallel coordinates curve for the Subspace KNN algorithm also displays recognizable patterns as shown in Fig. 20. This suggests that while the algorithm catches the crucial properties, it may not be as selective as the Fine KNN approach.

A comprehensive comparison of machine learning techniques for arm exercise monitoring produced insightful results. With an accuracy of 91.3 %, the Fine KNN algorithm performed significantly better than the others. Its ROC curve, scatter plot analysis, and parallel coordinates curve all demonstrated its enhanced capacity to discern between various workout patterns, supporting its superior performance. On the other hand, the Subspace KNN method performed admirably even with a little lower accuracy of 89 %. Its capacity to identify workout patterns was indicated by the ROC curve, scatter plot, and parallel coordinates curve studies; nevertheless, its degree of separation was somewhat less than that of the Fine KNN method. This study is motivated by prioritizing simple and computationally efficient models. Even though RF is a reliable and popular method, this study aims to select more simplified models with shorter training times and less complexity. This strategic choice emphasized practical considerations over the wider range of algorithmic capabilities, in line with the particular requirements of investigation.

Boosted Trees and Quadratic SVM algorithms, on the other hand, performed worse, with respective accuracies of 85.5 % and 85.2 %. Their proficiency in evaluating arm activities was demonstrated by the ROC curves, scatter plots, and parallel coordinate curves; however, the Fine KNN and Subspace KNN algorithms were shown to be superior options. The study's value is highlighted by its careful examination of several algorithms, which offer a standard for the use of machine learning in wearable fitness devices. But it's important to acknowledge the limitations. It is important to take into account any potential biases in the dataset, sensor accuracy limits, and the generalizability of the results. The conversation would be enhanced by placing this study in a larger perspective within the field of wearable fitness technology research and comparing the findings with those of other exercise monitoring techniques. This would provide a more comprehensive understanding of the study's implications. The chosen algorithms fine KNN boosted trees, quadratic support vector machines (SVM), Subspace KNN, and boosted trees offer unique advantages that encourage their use in the course of research. Subspace KNN and fine KNN are good for sensitive exercise monitoring because they are good at recognizing local patterns and adjusting to a variety of datasets. Quadratic SVM effectively manages non-linear correlations in the data, while boosted trees use ensemble learning to improve prediction accuracy. The study conducts a comparative analysis with alternative exercise monitoring techniques to highlight the unique benefits of the chosen algorithms and offer a thorough comprehension of their effectiveness within the study's parameters.

Table 2 presents a comparison of the current research with some other relevant projects in terms of the sensor used for data collection, the machine learning algorithm applied, the task performed, the involvement of hardware, the development of a mobile app as a user interface and the accuracy achieved for classifying the exercise data.

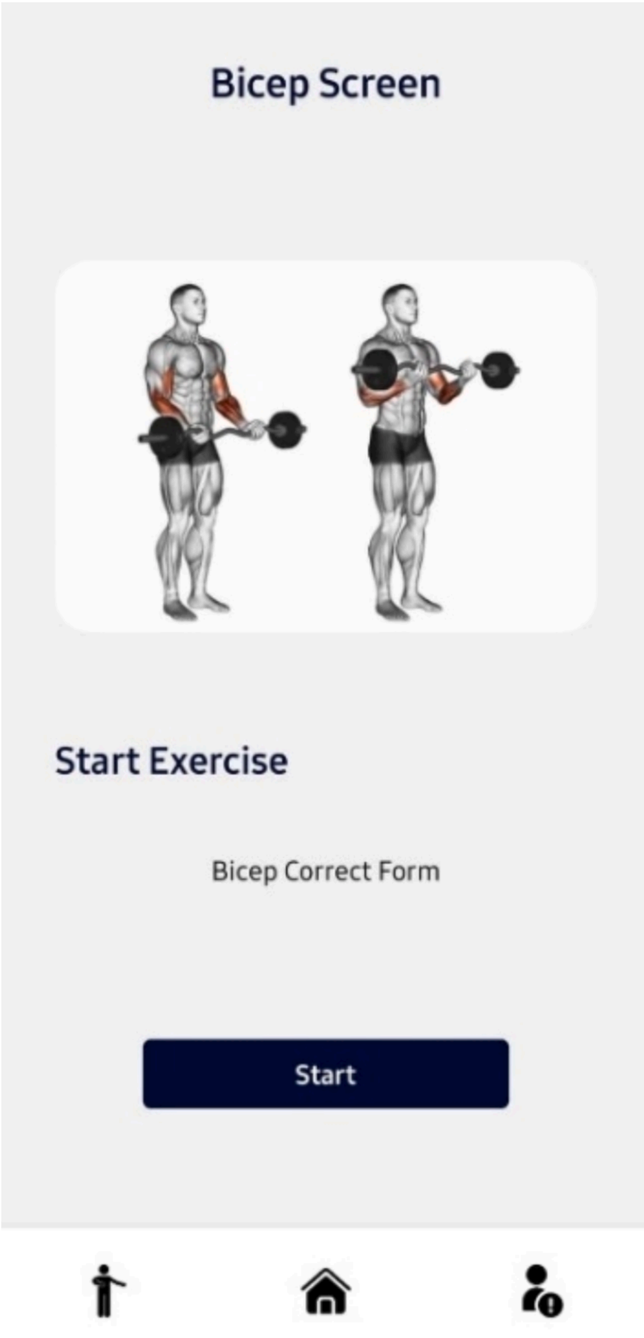

Fig. 12. The App shows the Predicted Output.

5. Conclusion and future work

In conclusion, analysis of arm exercises utilizing wrist-worn bands demonstrates the potential of Boosted Trees, Quadratic SVM, Subspace KNN, and Fine KNN algorithms. The study's findings show the potential of machine learning algorithms and wristbands with the MPU6050 sensor for assessing and monitoring arm activities. The findings show that machine learning methods, in particular, the Fine k-nearest neighbors (KNN) algorithm, can accurately identify various arm exercises with a high level of 91.3 % accuracy as compared to the others in which Boosted Trees which has 85.5 % accuracy, and Subspace KNN which has 89 % accuracy, and Quadratic SVM which has 85.2 % accuracy. This demonstrates how wrist-worn bands can gather motion data practically and unobtrusively. The results of this study have important

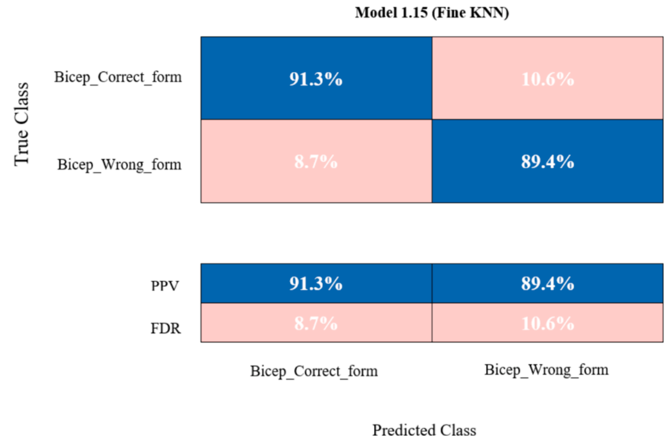

Fig. 13. Confusion Matrix of Fine KNN.

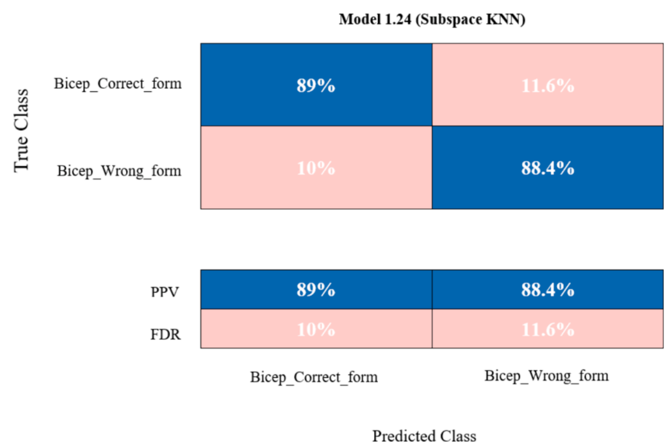

Fig. 14. Confusion Matrix of Subspace KNN.

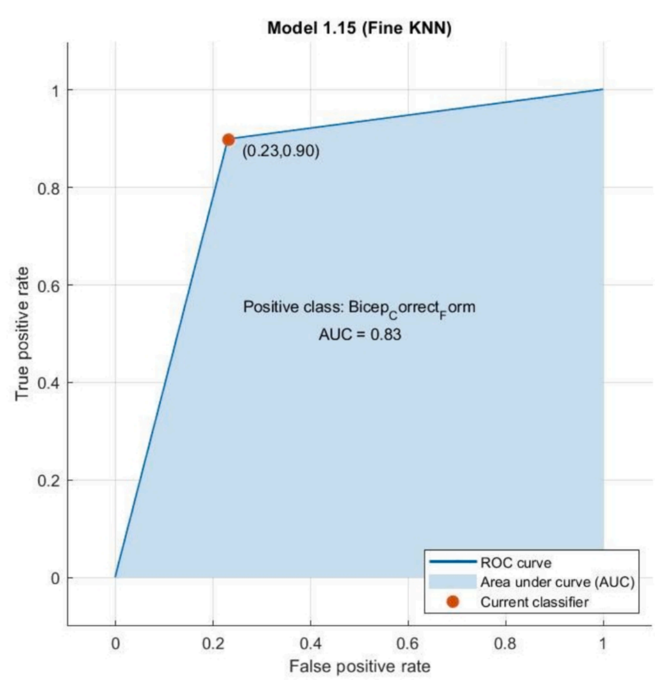

Fig. 15. ROC Curve of Fine KNN.

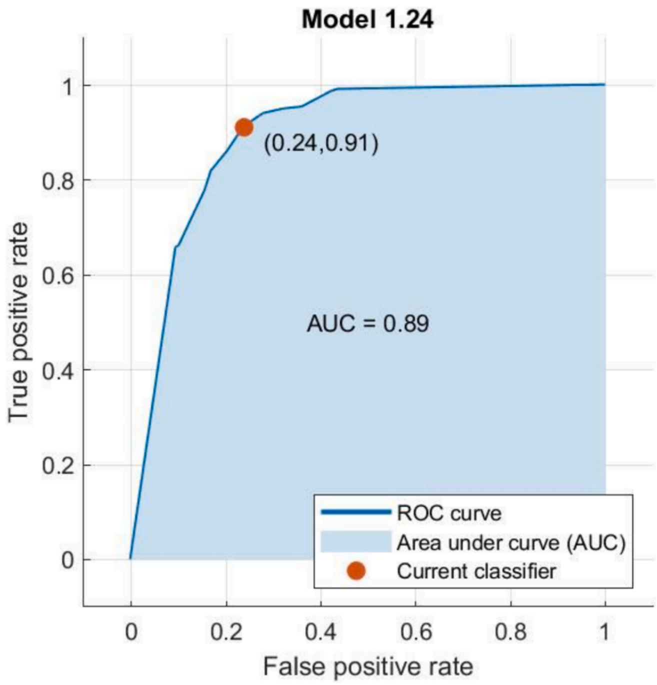

Fig. 16. ROC Curve of Subspace KNN.

ramifications for at-home workout regimens, especially when access to qualified trainers may be restricted. By using machine learning algorithms and wrist-worn bands, people can improve the tracking of their exercise performance, maintain good posture, and lower their risk of developing chronic conditions like tendinitis and back pain. With the integration of cloud infrastructure and a NODEMCU ESP8266, the created software prototype makes real-time data collecting, storage, and analysis easier. Because of this, users may get immediate feedback on how well they're exercising, which helps them advance and achieve fitness goals.

The possibilities of data processing and visualization are further improved by the usage of the ThingSpeak platform and interaction with MATLAB. Although the study's findings are encouraging, certain issues require further investigation. The robustness and generalizability of the machine learning models can be improved by expanding the dataset with a higher sample size and including different kinds of wrist-worn bands. Furthermore, long-term research to evaluate the efficiency of tailored exercise routines based on the gathered data will offer insightful information. This study confirms the potential of wrist-worn bands and machine-learning algorithms for monitoring and evaluating arm activities. Additional developments in this area could fundamentally alter exercise evaluation, program design, and monitoring, ultimately enhancing exercise performance, security, and fitness outcomes for each individual. According to evaluations of the ROC curve, scatter plot, and parallel coordinates curve, the Fine KNN algorithm demonstrated more accuracy and stronger discriminative power. The Subspace KNN algorithm, on the other hand, also showed satisfactory performance and may be thought of as an alternate strategy. It is advised to do additional research and experiments to examine the possibility of additional machine learning algorithms and to improve the current models for increased precision and performance while assessing arm exercises.

Future research in this area may concentrate on increasing the algorithm's classification accuracy for arm exercises for all. Using more complex features or training the algorithms on larger datasets could accomplish this. With the help of this feature, users will be able to get

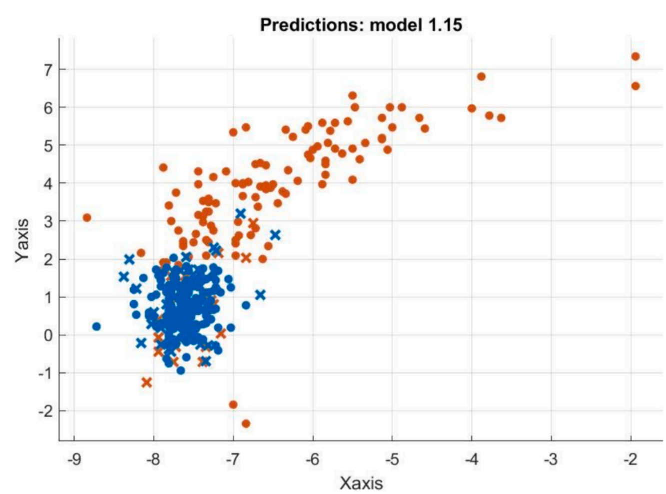

Fig. 18. Scatter Plot of Fine KNN.

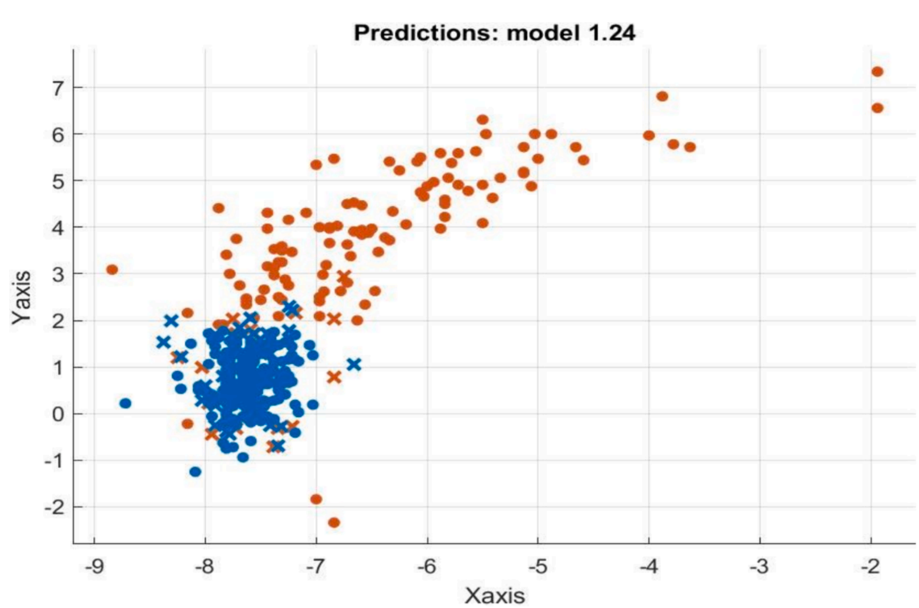

Fig. 17. Scatter Plot of Subspace KNN.

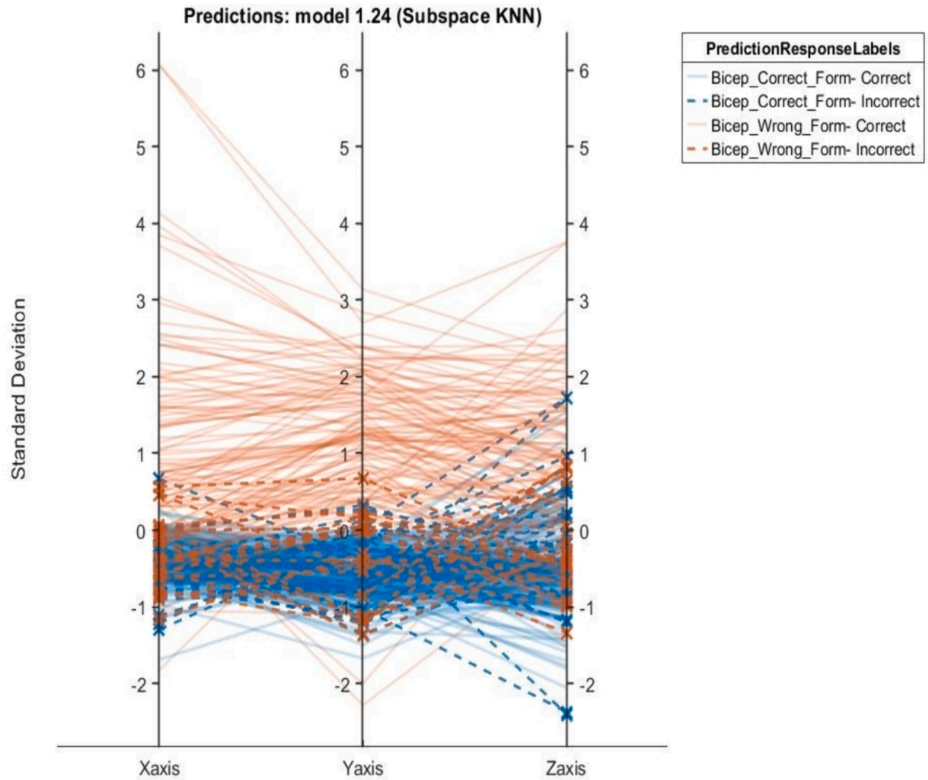

Fig. 19. Parallel Coordinates of Subspace KNN.

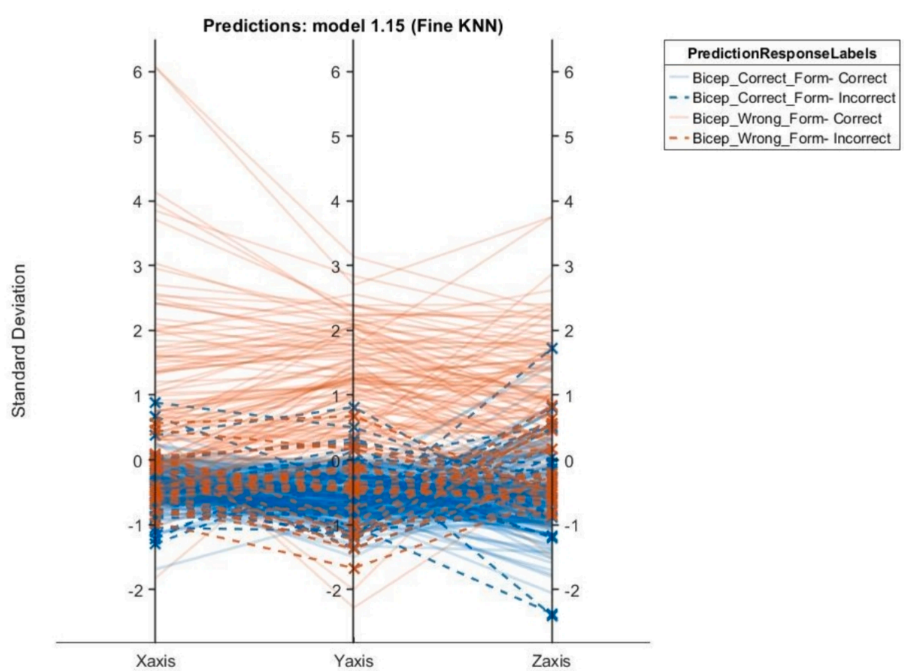

Fig. 20. Parallel Coordinates of Fine KNN.

feedback on how they performed during a workout and receive personalized workout recommendations. The time it takes for the system to determine the status of an exercise after the user completes it is now 15 s. The system's delay can also be minimized and it is suggested that the reduction of delay can be achieved through algorithm enhancements and the integration of a more efficient microcontroller.

Funding statement

This research was funded by Warsaw University of Technology, Faculty of Mechanical and Industrial Engineering from funds for the implementation of KITT4SME (platform-enabled KITs of arTificial intelligence FOR an easy uptake by SMEs) project under the European Commission H2020 Program, GA 952119 (https://kitt4sme.eu/). The

Table 2
Comparison of current work with related projects in the literature.

Ref. (year)	Sensors/signal used	Machine learning Technique	Task	Hardware	Android App Development	Accuracy
Proposed work	MPU6050 on-chip accelerometer	Boosted trees, Quadratic SVM, Subspace KNN, Fine KNN	Arm exercise classification	Yes	Yes	91.3 %
[10] (2023)	Electromyographic (EMG) signal	Decision trees, SVM, KNN	Arm workout classification	Yes	No	90 %
[35] (2021)	Accelerometer based wearable sensors	SVM, RF, Multilayer perceptron	Detect and track rehabilitation exercises	Yes	No	80 %
[36] (2021)	Wearable based motion capture system	SVM	Classifying single-axis spinal motion using data streams from stretch sensors for exercise recognition	Yes	No	85 %
[37] (2021)	Data gloves composed of flex sensors, force-resistive sensors, and IMU	Decision tree XGBoost, Logistic regression	Automated assessment in-home rehabilitation session	Yes	Yes	85 %

Article Processing Charge (APC) was paid by Warsaw University of Technology within the Excellence Initiative: Research University (IDUB) program. This research work was also funded by the Researchers Supporting Project No. (RSP2024R363), King Saud University, Riyadh, Saudi Arabia.

CRediT authorship contribution statement

Aamer Bilal Asghar: Conceptualization, Data curation, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. **Maham Majeed:** Conceptualization, Data curation, Methodology, Software, Writing – original draft, Writing – review & editing. **Abdullah Taseer:** Conceptualization, Data curation, Methodology, Software, Writing – original draft. **Muhammad Burhan Khan:** Conceptualization, Data curation, Methodology, Software, Writing – original draft. **Khazina Naveed:** Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Mujtaba Hussain Jaffery:** Conceptualization, Formal analysis, Methodology, Project administration, Supervision. **Ahmed Sayed Mohammed Metwally:** Conceptualization, Funding acquisition, Methodology, Project administration. **Krzysztof Ejsmont:** Conceptualization, Data curation, Funding acquisition, Methodology, Project administration, Software, Supervision, Writing – original draft, Writing – review & editing. **Mirosław Nejman:** Conceptualization, Funding acquisition, Methodology, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Sabry F, Eltaras T, Labda W, Alzoubi K, Malluhi Q. Machine learning for healthcare wearable devices: the big picture. Journal of Healthcare Engineering 2022;18:2022.
[2] Zhang S, Li Y, Zhang S, Shahabi F, Xia S, Deng Y, et al. Deep learning in human activity recognition with wearable sensors: a review on advances. Sensors 2022;22(4):1476.
[3] Ali A, Ashfaq M, Qureshi A, Muzammil U, Shaukat H, Ali S, et al. Smart detecting and versatile wearable electrical sensing mediums for healthcare. Sensors 2023;23(14):6586.
[4] Ho WT, Yang YJ, Li TC. Accuracy of wrist-worn wearable devices for determining exercise intensity. Digital Health 2022;8. 20552076221124393.
[5] Zhang JH, Macfarlane DJ, Sobko T. Feasibility of a chest-worn accelerometer for physical activity measurement. J Sci Med Sport 2016;19(12):1015–9.
[6] Tan YH, Liao Y, Tan Z, Li KH. Application of a machine learning algorithms in a wrist-wearable sensor for patient health monitoring during autonomous hospital bed transport. Sensors 2021;21(17):5711.
[7] Sevil M, Rashid M, Maloney Z, Hajizadeh I, Samadi S, Askari MR, et al. Determining physical activity characteristics from wristband data for use in automated insulin delivery systems. IEEE Sens J 2020;20(21):12859–70.
[8] Lin WY, Verma VK, Lee MY, Lai CS. Activity monitoring with a wrist-worn, accelerometer-based device. Micromachines 2018;9(9):450.
[9] Asghar AB, Majeed M, Taseer A, Khan MB, Naveed K, Jaffery MH, et al. Comparative performance analysis of machine learning algorithms for arm and shoulder exercises using wrist-worn band. IEEE Access 2023.
[10] Chun S, Kim S, Kim J. Human arm workout classification by arm sleeve device based on machine learning algorithms. Sensors 2023;23(6):3106.
[11] Rigoni M, Gill S, Babazadeh S, Elsewaisy O, Gillies H, Nguyen N, et al. Assessment of shoulder range of motion using a wireless inertial motion capture device—a validation study. Sensors 2019;19(8):1781.
[12] Fraysse F, Post D, Eston R, Kasai D, Rowlands AV, Parfitt G. Physical activity intensity cut-points for wrist-worn GENEActiv in older adults. Frontiers in Sports and Active Living 2021;15(2):579278.
[13] Shei RJ, Holder IG, Oumsang AS, Paris BA, Paris HL. Wearable activity trackers–advanced technology or advanced marketing? Eur J Appl Physiol 2022;122(9):1975–90.
[14] Kang JI, Choi HH, Jeong DK, Choi H, Moon YJ, Park JS. Effect of scapular stabilization exercise on neck alignment and muscle activity in patients with forward head posture. J Phys Ther Sci 2018;30(6):804–8.
[15] Turner A, Jackson D, Officer E, Boyne-Nelson C, Zielinska Z, Dinraj D, et al. Can wrist-worn devices and a smartphone application influence arm activity in children with unilateral cerebral palsy? A proof-of-concept study. Frontiers in Rehabilitation Sciences 2023;30(3):1060191.
[16] Giurgiu M, Ketelhut S, Kubica C, Nissen R, Doster AK, Thron M, et al. Assessment of 24-hour physical behaviour in adults via wearables: a systematic review of validation studies under laboratory conditions. Int J Behav Nutr Phys Act 2023;20(1):1–2.
[17] Seng KP, Ang LM, Peter E, Mmonyi A. Machine learning and AI technologies for smart wearables. Electronics 2023;12(7):1509.
[18] Covi E, Donati E, Liang X, Kappel D, Heidari H, Payvand M, et al. Adaptive extreme edge computing for wearable devices. Front Neurosci 2021;11(15):611300.
[19] Tan TH, Wu JY, Liu SH, Gochoo M. Human activity recognition using an ensemble learning algorithm with smartphone sensor data. Electronics 2022;11(3):322.
[20] Taghanaki SR, Rainbow M, Etemad A. Wearable-based Classification of Running Styles with Deep Learning. arXiv preprint arXiv:2109.00594. 2021 Sep 1.
[21] de Vries WH, Amrein S, Arnet U, Mayrhuber L, Ehrmann C, Veeger HE. Classification of wheelchair related shoulder loading activities from wearable sensor data: a machine learning approach. Sensors 2022;22(19):7404.
[22] Naeem M, Yu J, Aamir M, Khan SA, Adeleye O, Khan Z. Comparative analysis of machine learning approaches to analyze and predict the COVID-19 outbreak. PeerJ Comput Sci 2021;16(7):e746.
[23] Baldassarri S, García de Quirós J, Beltrán JR, Álvarez P. Wearables and Machine Learning for Improving Runners' Motivation from an Affective Perspective. Sensors 2023. Feb 1;23(3):1608.
[24] Nair BB, Sakthivel NR. An upper limb rehabilitation exercise status identification system based on machine learning and IoT. Arab J Sci Eng 2022;47(2):2095–121.
[25] Gomez-Arrunategui JP, Eng JJ, Hodgson AJ. Monitoring arm movements post-stroke for applications in rehabilitation and home settings. IEEE Trans Neural Syst Rehabil Eng 2022;10(30):2312–21.
[26] Kushsairy AK, Malik MA, Zulkhairi MY, Nasir H, Khan S. Real time monitoring system for upper arms rehabilitation exercise. In2015 IEEE 3rd International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA) 2015 Nov 24 (pp. 1-5). IEEE.
[27] Ambar R, Ahmad MS, Jamil MA. Design and development of arm rehabilitation monitoring device. In5th Kuala Lumpur International Conference on Biomedical Engineering 2011: (BIOMED 2011) 20-23 June 2011, Kuala Lumpur, Malaysia 2011 (pp. 781-784). Springer Berlin Heidelberg.
[28] Nguyen M, Fan L, Shahabi C. Activity recognition using wrist-worn sensors for human performance evaluation. In2015 IEEE International Conference on Data Mining Workshop (ICDMW) 2015 Nov 14 (pp. 164-169). IEEE.
[29] Yoshida Y, Yuda E. Workout detection by wearable device data using machine learning. Appl Sci 2023;13(7):4280.
[30] Karmakar NC, Baghini MS. Embedded machine learning on accelerometer data for exercise classification. In2023 IEEE Applied Sensing Conference (APSCON) 2023 Jan 23 (pp. 1-3). IEEE.
[31] Yun SH, Kim HJ, Ryu JK, Kim SC. Fine-grained motion recognition in at-home fitness monitoring with smartwatch: a comparative analysis of explainable deep neural networks. InHealthcare 2023 Mar 24 (Vol. 11, No. 7, p. 940). MDPI.

[32] Ma C, Li W, Gravina R, Du J, Li Q, Fortino G. Smart cushion-based activity recognition: prompting users to maintain a healthy seated posture. IEEE Syst Man Cybern Mag 2020;6(4):6–14.
[33] Page EJ, Massey AS, Prado-Romero PN, Albadawi S. The use of self-monitoring and technology to increase physical activity: a review of the literature. Perspectives on Behavior Science 2020;43:501–14.
[34] Pardoel S, Kofman J, Nantel J, Lemaire ED. Wearable-sensor-based detection and prediction of freezing of gait in Parkinson's disease: a review. Sensors 2019;19(23):5141.
[35] Espinoza Bernal VC, Hiremath SV, Wolf B, Riley B, Mendonca RJ, Johnson MJ. Classifying and tracking rehabilitation interventions through machine-learning algorithms in individuals with stroke. Journal of Rehabilitation and Assistive Technologies Engineering 2021;28(8). 20556683211044640.
[36] Chen J, Caviedes J, Li B. Classification of single-axis spinal motion using a wearable system of stretch sensors for at-home physical therapy. In2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) 2021 Nov 1 (pp. 7404-7407). IEEE.
[37] Sarwat H, Sarwat H, Maged SA, Emara TH, Elbokl AM, Awad MI. Design of a data glove for assessment of hand performance using supervised machine learning. Sensors 2021;21(21):6948.