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Smart Wearable to Prevent Injuries in Amateur Athletes in Squats Exercise by Using Lightweight Machine Learning Model

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Abstract: An erroneous squat movement might cause different injuries in amateur athletes who are not experts in workout exercises. Even when personal trainers watch out for the athletes' workout performance, light variations in ankles, knees, and lower back movements might not be recognized. Therefore, we present a smart wearable to alert athletes whether their squats performance is correct. We collect data from people experienced with workout exercises and from learners, supervising personal trainers in annotation of data. Then, we use data preprocessing techniques to reduce noisy samples and train Machine Learning models with a small memory footprint to be exported to microcontrollers to classify squats' movements. As a result, the k-Nearest Neighbors algorithm with k = 5 achieves an 85% performance and weight of 40 KB of RAM.

Keywords: squat analysis; lifting loads; ergonomics risk; intelligent systems; back injuries; embedded systems

Citation: Arciniega-Rocha, R.P.; Erazo-Chamorro, V.C.; Rosero-Montalvo, P.D.; Szabó, G. Smart Wearable to Prevent Injuries in Amateur Athletes in Squats Exercise by Using Lightweight Machine Learning Model. *Information* **2023**, *14*, 402. https://doi.org/10.3390/info14070402

Academic Editors: Anirban Bandyopadhyay and Kanad Ray

Received: 19 May 2023
Revised: 26 June 2023
Accepted: 3 July 2023
Published: 14 July 2023

1. Introduction

The training squat process aims to adequately strengthen the muscles around the knees and hip joints and fortify the lower back. Also, lifting loads from the ground could be an excellent exercise to activate muscles to be applied in different sports [1,2]. The normal range during knee flexion is between 90 and 130 degrees [3]. However, the risk of getting injured is high in the first few attempts until the athlete learns to perform the move adequately. This mostly occurs in amateur athletes, for whom exercising is not their primary job, who work out several days a week, mainly to be healthy [4]. Therefore, the common mistakes when learning to perform squats are: (i) starting by folding the knees, which puts pressure on the knee ligaments; (ii) allowing the knees to pass over the feet, since this might put more pressure on the lower back; (iii) the feet are unbalanced, which might affect knees and hips; (iv) allowing the knees to point outwards or inwards, which might affect ankles and hips; and (v) failing to reach at least 90 degrees when the knee is flexed [5]. As a result, these issues performing squats could be summarized by the following three main mistakes: knee abduction position, knee adduction position, and wrong angle flexion. Figure 1 shows the right and wrong knee positions for squats. Considering the identified mistakes during squatting, evidence suggests that misalignment in the knee joints can increase the risk of knee injuries, particularly to the ligaments and cartilage. The main health problems in the knee produced as a result of these issues include Anterior Cruciate Ligament (ACL) Injury, Medial Collateral Ligament (MCL) Injury, Meniscus Tear, Patellar Tendinitis, and Patellofemoral Pain Syndrome [6].

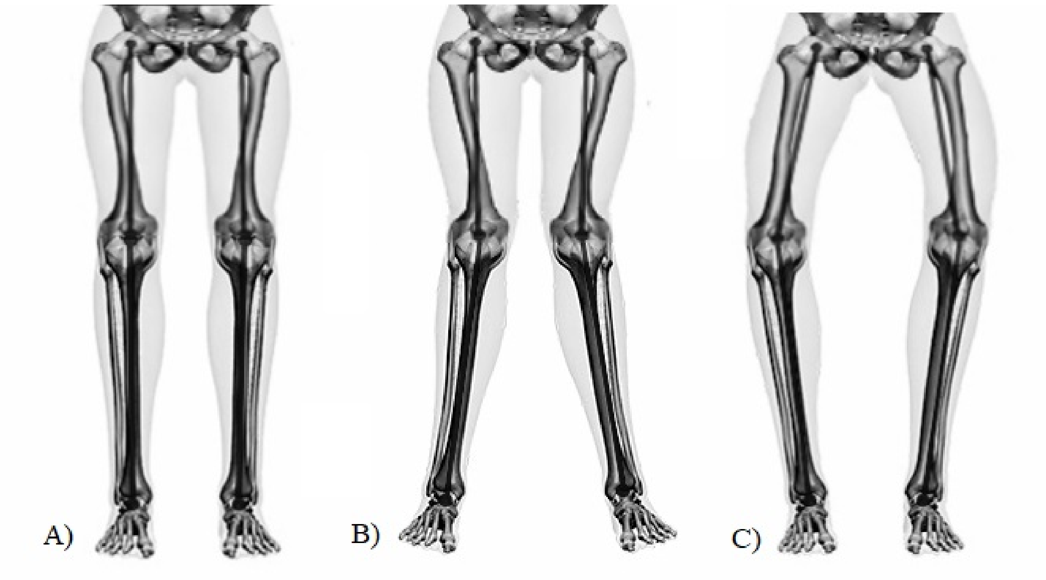

Figure 1. Ergonomic position in the movement. (**A**) Correct ergonomic knee position. (**B**) Knee abduction ergonomic position. (**C**) Knee adduction ergonomic position.

A good knee biomechanical technique during squats is based on the proper support of the feet, which should be separated to shoulder width with the toes facing forward [7]. Additionally, the knees should follow the direction of the feet and should not exceed the level of the toes' tips to prevent internal rotation [8]. Conversely, squats may require weightlifting from the ground to maintain the same ergonomic posture as squats and avoid future illness. Figure 2 depicts the proper posture during the activity, beginning with separated legs and placing the feet at shoulder level, followed by knee flexion while maintaining a straight back posture (*Figure 2 was purchased by the authors in https://sp.depositphotos.com/114062280/stock-photo-squats-on-his-chest.html (accessed on 25 November 2022) and modified by them to adapt it to the interests of the proposed research*). In this scenario, training techniques for muscle conditioning and posture are required in the sports industry, where managers and athletes focus on improving the kinematics and kinetics of athletes [9]. Therefore, bio-mechanical analysis might also minimize athletes' risks and possible future illnesses [10,11].

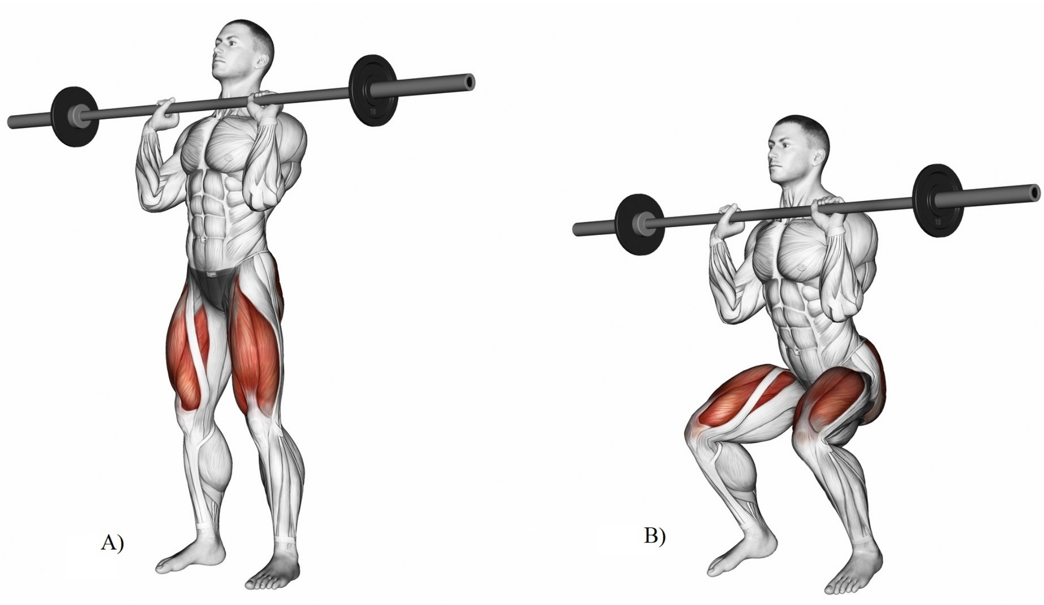

Figure 2. Ergonomic position in squats. (**A**) Squat starting position. (**B**) Recommended squat depth and body ergonomic position.

High-performance centres for athletes commonly use inertial measurement units (IMUs) to determine the flexion/extension angle of the knee joint, defining it as the angle between the upper and lower leg along the main axis of relative motion [12,13]. Furthermore, alternative technologies, such as cameras or Kinect, are helpful tools in sports. Unfortunately, they have specific requirements and traditional gyms do not provide the support needed, such as isolated environments and fixed locations without vibrations. For this reason, wearables are suitable solutions for designing individual scenarios in which several amateur athletes work simultaneously.

Following the trend of presenting individual solutions when people are working out necessitates that wearables make decisions locally to avoid bottlenecks in the communication channel and sharing unnecessary information that the wearable can handle itself. This decentralized computing architecture also provides a secure environment where the information stays safe on the device and specific information can only be shared with another device. Therefore, machine learning (ML) models allow patterns in data to be identified, and with current microcontrollers, the wearable can make inferences locally. Furthermore, each user could have a personal trainer on the device to alert them if their squat movement is incorrect, decreasing the chance of injury.

Based on the factors above, this research aims to develop a smart wearable to classify biomechanic movements when amateur athletes perform squats [14]. Therefore, the wearable comprises a microcontroller, battery, RF wireless communications, and sensors. The collected data were annotated by personal trainers to train different machine learning (ML) models. Next, the models were tested to determine the most suitable solution based on computational metrics, such as memory consumption and execution time. Finally, the model was exported to the wearable to be tested in real-trial conditions and to check the device's accuracy. In short, the main contributions of these works are presented as follows:

- Present a novel ML workflow running on the device to make inferences locally and prevent injuries in amateur athletes.
- A fair comparison between classical ML models and Deep Learning architectures to be exported in wearables.

The rest of the paper is organized as follows: Section 2 shows the background section and related works. Section 3 presents the wearable electronic design. The ML workflow is presented in Section 4. The results are shown in Section 5. Lastly, Section 6 shows the conclusions and future works.

2. Related Works

Several studies have shown how the kinematics analysis might describe the knee, hip, and ankle movements when athletes perform squats. Russell et al. [15] presented a Preliminary Comparison of Front and Back Squat Exercises to determine the connection between knee extensor and lower back injuries during squats. The research demonstrated a similar demand for muscular activity in the muscles around the knee and the back muscles. Horan et al. [16] established a study for single-leg kinematics in a group of young people. It identified the reduction of movement with aging. Raisanen et al. [17] presented an evaluation of young athletes through Frontal Plane Knee Control. The research used two-dimensional video analysis and subjective visual assessment by a physiotherapist. For their part, Ajdaroski et al. [18] conducted an analysis of a device used to measure knee joint angles during movements. Their study validates the ability of commercially available inertial measurement units to measure knee joint angles in a dynamic test.

The wearable biosensors were studied by Teague et al., who presented a system used to monitor knee joints through Multimodal sensing. It is two-microcontroller-based, using multi-microphone joint acoustics and lower-rate electrical bioimpedance (EBI) for multimodal knee health monitoring [19]. In addition, Faisal et al. created a Knee Monitoring System with a Low-Cost Multi-Sensor-Based Smart Wearable to monitor and assess the knee joint and mobility through motion, temperature, pressure, and galvanic skin response sensors to evaluate knee joints during different sports activities [20]. Following this field, an Automatic Classification of Squat Posture Using Inertial Sensors was presented by Lee et al., in which using conventional machine learning and deep learning were compared with the results obtained by an IMU to measure the kinematics of the knee [21].

Even though the works mentioned above provide evaluation systems for squat analysis, they also indicate the reason that squat analysis remains an open problem due to the need to create devices capable of evaluating and making decisions with the received data from sensors to save computational resources and reduce the volume of data transmission.

3. Wearable Design

The design of the wearable is illustrated in this section to describe all systems and components. The wearable is designed to be composed of three main stages: (i) system requirements, (ii) sensor selection, and (iii) electronic diagram connection. The design of the developed device involves the use of several stages, as described in Figure 3.

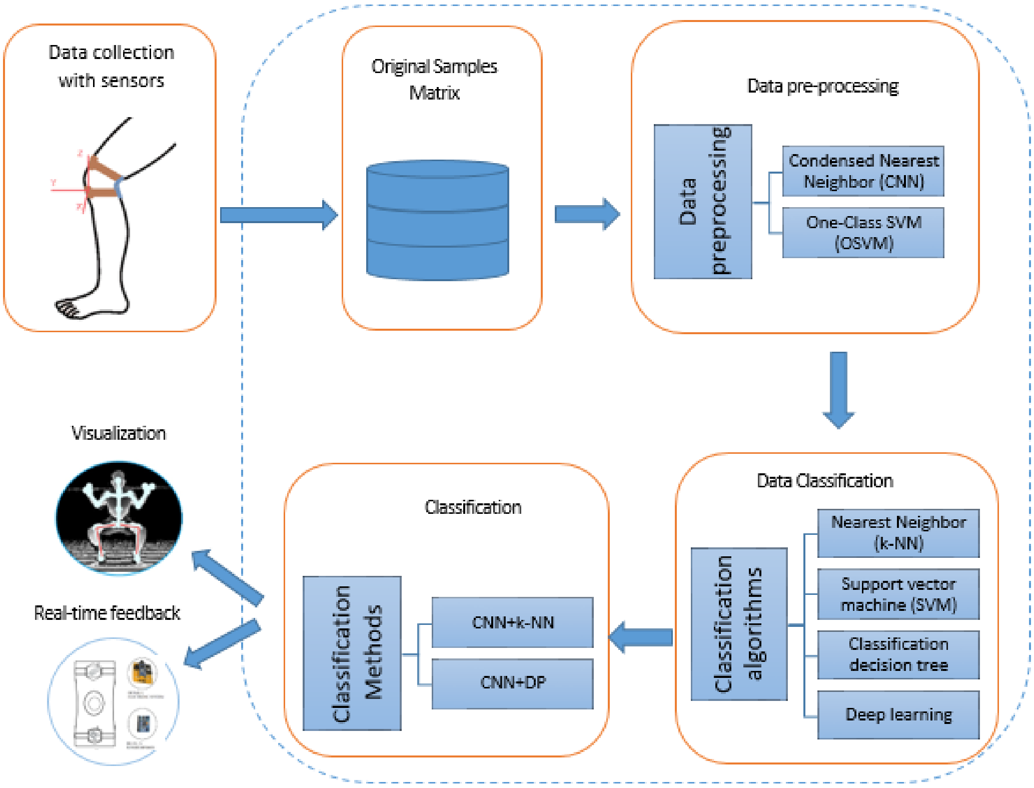

Figure 3. Developed electronic system scheme.

3.1. Human Subject Data Analysis

Good human subject analysis data for amateur athletes during squats can provide valuable insights into performance, injury prevention, individualized training, performance optimization, and motivation. It allows coaches, trainers, and athletes to make educated decisions and take specific actions to improve athletic performance.

The femorotibial joint has flexion and extension movements of the knee, with an external rotation during flexion and internal rotation during extension. The activation of the quadriceps and hamstrings will be determined by the degree of knee flexion, with 90-degree flexion activating the quadriceps the most [10].

The V-method based on IEEE Standard 29148 is used for strategic device requirements selection, which focuses on stakeholders' utility and validation stages for system definition [22]. Figure 4 shows the steps in human data processing and the necessary stages for system implementation and evaluation, comparing the input parameters and system performance evaluated under expert supervision [23].

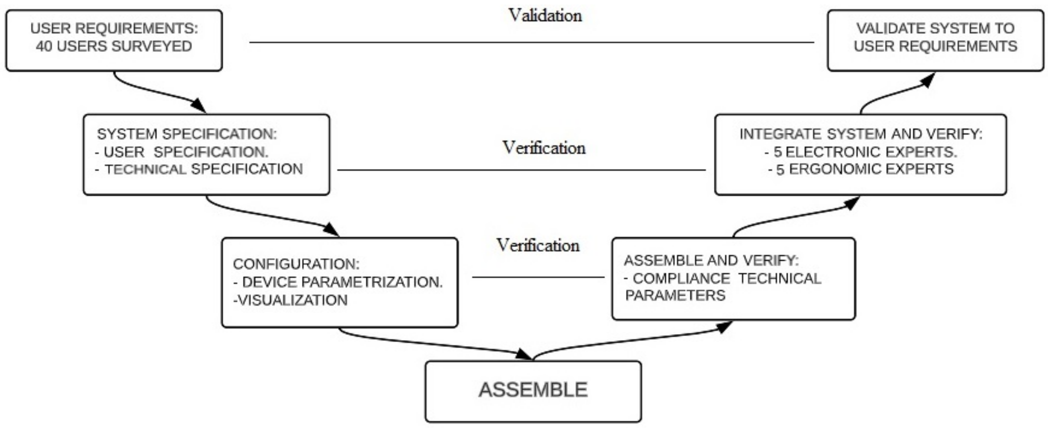

Figure 4. Applied V-model for system design.

The V-model allows the system to collect the data used for human subject analysis data to provide helpful information about inexperienced athletes' results throughout practice sessions. It enables coaches and trainers to evaluate athletes' speed, agility, strength, endurance, and technique performance. It can help sports people identify potential injury risks and analyze movement patterns, biomechanics, and load distribution. The parametrical set can provide individualized information that can be used to optimize training programs to maximize performance gains, improve training efficiency, and measure athletes' progress and performance.

3.2. System Requirements

The main goal in product design is always to reduce the cost and make a trusted device to fulfil the requirements of the project. In this way, Table 1 shows the functionality and user requirements based on the IEEE 29148 standard [22].

Table 1. System Requirements.

Systems and Software Engineering—Requirements Engineering		
Requirements	**Priority**	**Description**
Ease of use	High	Defining the needs and requirements of stakeholders
Error wrong posture system alarm	High	Define and perform activities related to security
The system must have a visualization interface	High	Define and perform activities related to understanding and documenting the relationship between the user and the system
The data analysis must be in real time	High	Perform activities related to classifying, reviewing and prioritizing the requirements
The system must have lightweight	High	Perform activities related to requirements in the architecture definition
The system must measure the knee angle	High	Perform activities related to requirements in the validation phase
The system must measure the deviation angle	High	Perform activities related to requirements in the validation phase
The computational load must be as low as possible	Medium	Define and perform activities related to requirements in other technical processes

3.3. Sensor Selection

For correct system functionality, the system could collect data for the knee to determine if the knee exceeds the tip of the foot or if it has a deviation of the knee (abduction or adduction) when performing the exercise. It might also identify the internal flexion angle.

A benchmark test determines the correct sensor, compares the characteristics, and chooses the feasible sensor for applications. Table 2 shows the features of the flexible sensor, the Flex Sensor 4.5″ manufactured and distributed from the USA by ALSROB, which meets the requirements and allows conversion of the data with a response of 30 kΩ to 70 kΩ in a range of 0 to 130 flexion degrees. Besides, the sensor MPU 6050 is used to determine the knee position, which allows the measures from the accelerometer and gyroscope to be used together.

Table 2. Sensors characteristics.

Sensors Technical Features		
Requirements	**Flex 4.5″**	**MPU 6050**
Reliability	High	High
Scope	30 kΩ to 70 kΩ	±250, ±500, ±1000, ±2000 °/seg
Consumption	—	Low
Operating temperature range	−35 °C to 80 °C	−40 °C to +85 °C

The evaluation of the knee position is based on two parameters. The first one is the position of the knee concerning the tip of the foot (X-axis data from the sensor), and the second is the opening that is generated between the knees during the squat exercise (Y-axis data from the sensor); that is, abduction and adduction. The system uses a gyroscope MPU6050 sensor manufactured and distributed from China by WWZMDiB, to determine the orientation with gravity. It is connected to the microcontroller for data processing and decision-making. The MPU 6050 module is connected to the microcontroller's I2C module. The Flex sensor is a variable resistor that needs an analogue-to-digital converter to process the incoming data. Based on the principle proved by many previous researchers, which is established as the primary learning method in the brain and is based on symmetric bilateral movements and mirror-symmetric movements with homologous muscles activated simultaneously, it was determined to use the device on one knee at a time to ensure a cognitive ergonomy [14,24,25].

3.4. Sensor Calibration

It is necessary to obtain values according to how the sensor is bent to convert the voltage received from the Flex sensor to angles. Equation (1) shows the voltage divider to identify light voltage variations to be converted into degrees.

$$Vout = Vin.\frac{R1}{R1 + R2} \quad (1)$$

where:

Vout = Voltage given by the sensor.
Vin = Voltage Given by the source.
*R*1 = Static resistance.
*R*2 = Sensor variable resistance.

For the MPU-6050 sensor, the elimination of zero error is needed to determine the proper sensor calibration, and this process helps to determine the position at which the sensor is leveled. To solve this issue, one script was developed by Luis Rodenas et al. [26]. It calibrates the sensor uploading to the accel–gyro module and sets the flat and level positions. After initial calibration, the algorithm obtains the data and evaluates them for a few hundred readings, removing zero errors before starting the trial. The data evaluated from MPU-6050 compare the "Y" axis to determine the femorotibial angle and leg opening, as well as the value in the "X" axis to determine the reference between knee and tiptoe.

3.5. Voltage Source Supply

The system is placed on a knee pad and adequately covered to reduce any possibility of contact with the athlete's body. When the device is turned on, the complete system is running and communicating with the computer. Based on the specified requirements in the technical reports of each component, the total power is calculated using Equation (2).

$$IT = \sum_{i=1}^{n} Ie_i \quad (2)$$

where:

IT = total power supply.

Ie_i = Power needed for each component.

In order to complete a proper functioning system state, theoretical consumption requirements of the circuit components are considered. In this context, at a regulated level of 5 V, the power needed is: 40 mA for the microcontroller, the Flex sensor Flex needs 5 mA, the MPU6050 3.6 mA, nRF24L01 11.3 mA, and the buzzer 18 mA. As a result, the wearable needs at least 157.9 mA, supplied with 9 V of LiPo battery manufactured and distributed from China by Tenergy.

3.6. Wearable Device

The wearable knee pad provides a small space to implement the electronic device. Figure 5 shows the device architecture, considering the system as a total block and sending the data to the computer. The wearable consists of two small cases to protect the electronic components. In the frontal part, at the upper location, the controller system and voltage source are located and covered by the first case, which is fixed with a flexible band to the knee pad. The second flexible band is located in the lower part with the other case to fix the MPU 6050 sensor. This sensor is connected through flexible conductors to the I2C bus. The Sensor Flex 4.5″ is positioned at the rear part, which is connected to the analogue input A0 and the voltage source of the controller.

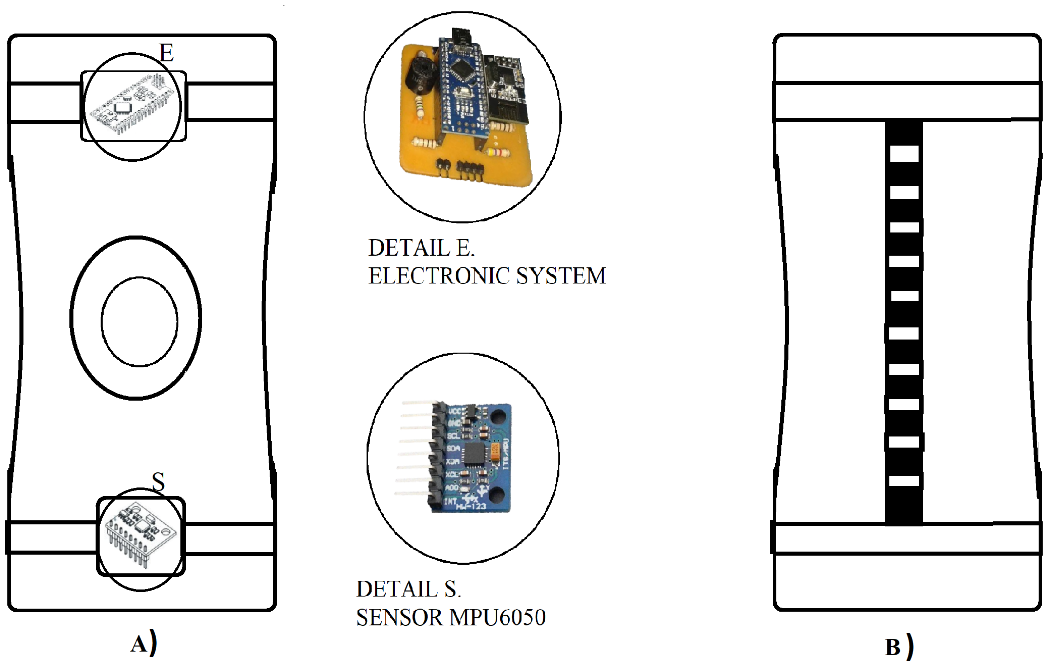

Figure 5. Wearable squat evaluation system arrangement. (**A**) Front view. Processor and MPU 6050 sensor location. (**B**) Back view. Sensor Flex 4.5″ location.

4. ML Workflow

Given that the electronic design was presented in the previous section, the data obtained need to be processed. This process starts with the use of preprocessing techniques like condensed nearest neighbour (CNN) and outlier detection models to remove noisy samples. Then, personal trainers annotate data to provide labels to the classifier. Furthermore, deep learning techniques with neural network models are also deployed to evaluate their performance.

4.1. Original Samples

The designed wearable was used in different fitness centres in which the Óbuda University has agreements to help amateur athletes, some of whom are part of the university. The data collection stage started with the selection of amateur athletes with experience performing squats. Then, the personal trainer evaluated each squat to annotate data. Conversely, the personal trainer supervised athletes without or lacking experience performing squats and recommended ways to improve the movement and avoiding injuries. As a result, the system could recognize two main common mistakes: the abduction or adduction of the knees due to their repetition during the performance. These issues increase the chance of injury in the lower back and legs. Therefore, label 1 represents an adequate squat, and labels 2 and 3 represent abduction or adduction issues. As a result, 40 people (15 inexperienced and 25 experienced amateur athletes) were tested to create a balanced dataset with 1200 samples.

4.2. Data Preprocessing

The electronic device detects when the accelerometer is descending; thus, it decides that the squat exercise has started. Then, it analyzes when the sensor is not descending anymore to recognize that the athlete is in the middle of the exercise. Next, it detects when the accelerometer ascends until the human finalizes the exercise. However, even when sensors are calibrated, some samples have errors and drift. These are called outliers, and they can affect the boundary decision of the ML models. Therefore, we selected two approaches to find and eliminate outliers [27]. The first approach is the prototype selection technique, where Condensed Nearest Neighbor (CNN) is an algorithm that retains the points closest to the decision's limits edge points [28]. The second approach uses outlier detection models. Those models can detect data with a different distribution than the rest. This process is carried out through an unsupervised analysis, and the model decides which samples need to be deleted. One-Class SVM (OSVM) is an algorithm that captures the density of the majority class and classifies examples using the extremes of the density function as an outlier [29]. The selection of the above-mentioned models was made via literature review, which shows the most representative algorithms in sensor data.

4.3. Classification Algorithms

The classification approaches include: (i) distances: the k-Nearest Neighbor (k-NN) algorithm, which associates a new instance with the training base and assigns it to the closest group according to its distance. (ii) Following models: the support vector machine (SVM) algorithm with kernel functions that serve as a mechanism of the input information to the algorithm. With this, it can work with any data. (iii) Heuristics: the classification decision tree algorithm is used. This algorithm seeks to divide the classification space into zones so that the patterns that belong to each zone are assigned to one of the available classes, and (iv) deep learning to find patterns data with fully connected neural network architectures.

5. Results

This section shows the adequate ML models to be exported into the wearable with a small memory footprint and the final device tested in real-trial conditions.

5.1. ML Workflow

We trained the classification algorithms with the original samples to discover the general classification accuracy. Therefore, Table 3 shows the classification metrics of each classification algorithm. It is essential to mention that the dataset was split into the training and test set.

Table 3. Original samples classification performance.

Classification Metrics	SVM	Decision Tree	k-NN	Deep Learning
Precision	0.67	0.62	0.67	0.70
Recall	0.66	0.61	0.66	0.59
F1-Score	0.65	0.62	0.66	0.60

Then, the One-CSM algorithm is applied to the original samples, which prunes the dataset to 780 instances, representing 40% of outliers. Next, the ML models were trained again to obtain the classification metrics with this new dataset. Table 4 shows that it is evident that each classifier had better results with this pruned dataset.

Table 4. Pruned dataset by One-SVM classification performance.

Classification Metrics	SVM	Decision Tree	k-NN	Deep Learning
Precision	0.73	0.72	0.81	0.79
Recall	0.72	0.73	0.81	0.77
F1-Score	0.73	0.71	0.81	0.76

The CNN algorithm also pruned the dataset significantly; in this case, the pruned dataset has 865 samples, representing over 30%. Furthermore, the classifier learned from this dataset much better and, in some cases, such as k-NN or the deep learning model, could recognize around 80% of good or incorrect squats. Table 5 shows the classification results.

Table 5. Pruned dataset by CNN classification performance.

Classification Metrics	SVM	Decision Tree	k-NN	Deep Learning
Precision	0.80	0.79	0.82	0.83
Recall	0.76	0.77	0.80	0.82
F1-Score	0.77	0.77	0.82	0.81

Figure 6 shows in three dimensions how the preprocessing techniques prune the dataset.

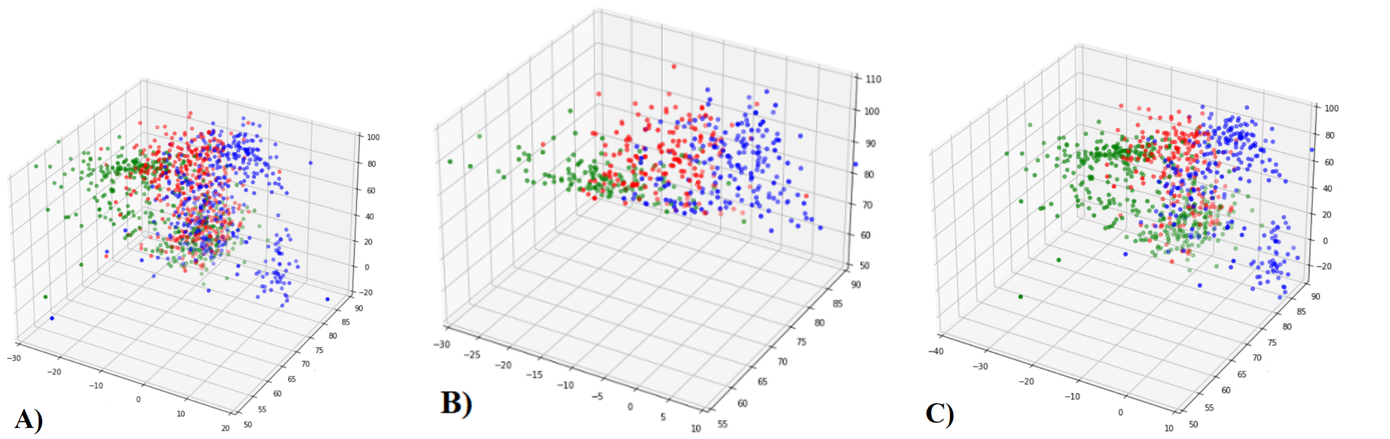

Figure 6. Outlier detection analysis. Blue dots: correct exercise, red dots: abduction detection, green dots: adduction detection. X-axis: MPU6050, Y-axis: MPU6050, and Z-axis: Flex sensor. (**A**) Original samples. (**B**) One-SVM. (**C**) CNN.

With the classification results obtained, k-NN and neural network models were demonstrated to be suitable for detecting good/incorrect squats. Therefore, each model was fine-tuned by its hyperparameters to improve its results or reduce complexity. Then, the k-NN algorithm tested its number of neighbours and the type of distance between two points. As a result, the model's accuracy is over 83% using the Minkowski metric and five neighbours. Conversely, the neural network model was more complicated to define the architecture suitable for reaching the highest classification score. Therefore, the architecture tested had two hidden layers, and the number of neurons was tested in several tests. As a result, Table 6 shows the neural network architecture with the highest classification score (82%).

Table 6. Neural network architecture.

Layer (Type)	Output Shape	Num. of Parameters
Input (Dense)	(None, 60)	240
Layer 1 (Dense)	(None, 80)	4880
Layer 2 (Dense)	(None, 40)	3240
Output (Dense)	(None, 3)	123

5.2. Wearable Device

Once the device was used, we exported both models, CNN + k-NN and CNN + DP, to determine their performance in real-trial conditions. The CNN + k-NN model needs to store samples in the memory's device, and the CNN and k-NN algorithms are deployed on the device. For its part, the DP model was quantized by using Tensorflow lite library to shirk the model and being able to run into the microcontroller. Then, both models were tested to identify their classification performance, memory footprint, and execution time. As a result, the CNN + k-NN model needs 40 Mbytes of RAM and takes 2.8 ms to predict the squat movement. Second, the CNN + DP model needs 1 MB of RAM and takes 12.2 ms, since its execution is more complex than the previous model. Lastly, in 50 real-trial experiments, both models perform similarly by recognizing the 90% good and incorrect squats, involving either adduction or abduction position. Therefore, we choose the CNN + k-NN model, since it is lightweight with fewer computational requirements.

The wearable is designed to work inside the wearable knee pad used in this research, as shown in Figure 7. Besides, the location of the sensors allows us to determine the position of the leg and how the activity is performed. In case of a bad ergonomic posture, the device produces a sonorous alarm to indicate to the users the need to recover a good posture. Additionally, the wearable recognizes the wrong position and sends the alarm flag to the computer for further visualization.

Figure 7. Electronic system tested in real-trial experiments.

6. Conclusions and Future Works

This research aimed to develop a smart wearable to detect good and incorrect squats. This system can analyze and decide the correct knee position and flexion to identify bad postures and indicate to the athlete the need to correct the posture. Also, the device sends the data to a computer. In short, the conclusions are presented and described as follows:

- This work supervised and analyzed the performed activities of people during squats, selecting the data to communicate to the computer to provide visualization.
- The correct measurement boundaries were selected to identify the correct posture through ML algorithms.
- The values were recognized to determine the adduction posture to set as a flag, which means a warning to activate the sonorous alarm to communicate the failed posture knee for visualization in the computer by RF.
- The values were recognized to determine the abduction posture to set as a flag, which means a warning to activate the sonorous vibrating alarm to communicate the failed posture knee for visualization in the computer via RF.

In future works, we look forward to implementing an artificial vision to join with the existing design to implement a robust ML, and even use this device to supervise ergonomic postures for hands.

Author Contributions: R.P.A.-R.: original draft preparation, formal analysis, and software; V.C.E.-C.: data curation, original draft preparation, and investigation; P.D.R.-M.: methodology, writing—review and editing; G.S.: resources, project administration; supervision; writing—review and editing, and funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Obuda University (protocol code: OE-DI-205,2023 approved on 28 November 2022).

Data Availability Statement: The data is unavailable due to privacy.

Conflicts of Interest: The authors declare no conflict of interest.

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