Towards a mobile system with a new wearable device and an AI application for walking and running activities

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Abstract. *Recognizing human activities from mobile applications is a challenging task due to the complexity of the context. Several healthcare applications consider wearable devices, including in the orthopedic area. Considering this context, we proposed a novel mobile application that can recognize walking activities with data collected by new wearable sensors on the user's leg. The wearable system collects the data, which is processed using Edge AI. Then, we propose to present the generated information as a digital twin considering the user's movements based on the sensor data. For this work, the wearable device and AI movement classification are operational, while the mobile application is still in development.*

1. Introduction

When we observe the scenario of the orthopedic area, we realize that the study of human body movement is a topic of great importance. Understanding the anatomical factors behind the mechanics of movement through its actors, such as muscles, bones, and joints (Lee et al. 2019) is of great importance and use in the medical and sports field. With the knowledge of these actors, it is possible to understand how movement is affected by several factors, including the interaction between ligaments, joints, and bones, muscle behavior, and fatigue.

In addition to analyzing any injury generated by these components, for example anterior cruciate ligament deficiency (ACLD) that affects human knee, it is also possible to act preventive against such damages and corrective help in healing and rehabilitation (Lu and Chang 2012). Deepening knowledge of the human body movement is also essential for sports and physical education. Such applied studies can be used to optimize and improve the training of athletes seeking better technique and movement efficiency.

This paper presents a new mobile application to capture and recognize walking and running activities in human movement. Data is collected by a wearable device composed of sensors and transmitted to the application, where an AI interprets and classifies them into a type of movement. At the same time, the data is also reproduced interactively in a virtual twin that replicates the user's activity. Figure 1 shows a representation of the system, including the wearable device and the mobile application.

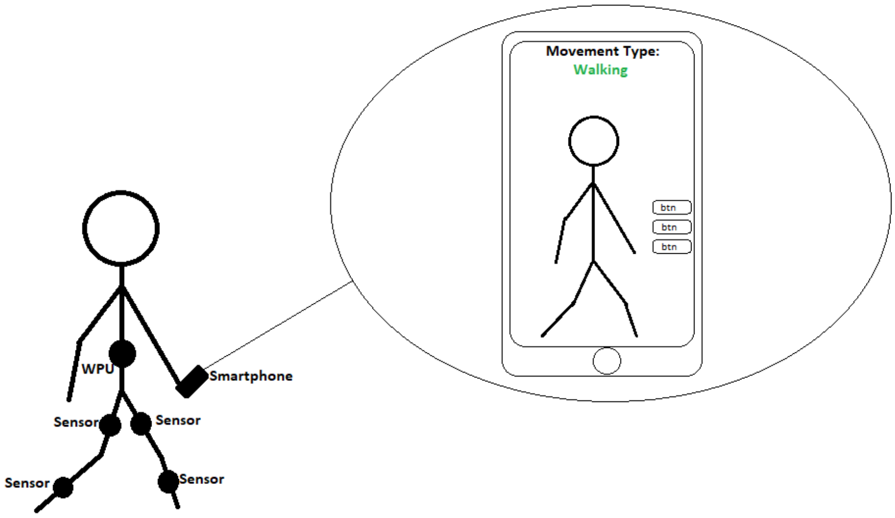

Figure 1. Application usage representation.

The main contribution of this work is:

- Proposal for a mobile platform composed of an integrated hardware and software solution. So, based on the data sent from a new wearable device and the aid of an AI algorithm, it reproduces the user's movements, in this scenario, walking and running activities.

1.1. Why not smartwatches?

Smartwatches are smart devices commonly used in healthcare and sports activities (Borowski-Beszta and Polasik 2020). These devices can provide information about a person's physical condition and performance in a sports activity (Zhuang and Xue 2019). In this context, smartwatches use the sensors present in their physical structure to predict this information (Schiewe et al. 2020; Taghavi et al. 2019). However, although these devices present interesting information to the user when carrying out a particular activity, there is an inevitable imprecision in this information because they use unique sensors.

The unique sensors located at a specific location of the user in the device, such as a gyroscope and accelerometer, use the movement pattern of one of the user's arms to identify an activity, for example, swimming (Cosoli et al. 2022). In this work, the authors used two smartwatches to identify swimming activity and minimize the inaccuracy of information in data classification. This point shows the disadvantage of the smartwatch: to increase accuracy, it needs more than one device.

Differently, our work seeks to identify walking and running activity by integrating four sensors on the user's leg together with a mobile application. In this form, the application presents real information about the activity. Therefore, we can identify more accurately than a single smartwatch.

1.2. Paper Organization

This work is organized as follows: Section 2 presents a theoretical review of related works found recently in the literature on AI and mobile applications centered on recognizing human activities. Section 3 presents the requirements used to create the application and information on how data is collected from the system. In Section 4, we have the analysis of the App developed. Finally, in Section 5, we present conclusions and future work.

2. Theoretical References and Related Work

In this section, we present the results of some literature reviews with an overview of tools and mobile apps in activity recognition with intelligent devices.

2.1. AI tools applications in human recognition

Artificial intelligence (AI) algorithms are fundamental for constructing new tools for recognizing human activities, such as human movement recognition based on deep learning (Wang et al. 2018). Together with information received by other devices and friendly visual interfaces, they form promising solutions for constructing a new system (Demrozi et al. 2020; Ann and Theng 2014).

Embedded devices with convolutional neural networks have the capability to detect and identify human activities. (Xu and Qiu 2021). However, applying these techniques can demand a lot of the device's computational power, which causes a restriction for some devices. Thus, the proposed app intelligently presents the information sent by wearable sensors to an android device, decentralizing tasks to optimize the resources used throughout the system.

2.2. Mobile applications

In the literature, we find examples of mobile applications that perform similar tasks. For instance, applications that perform this recognition in real-time (Lara and Labrador 2012). These applications are commonly used in healthcare (Zaki et al. 2020a). Apps developed in this context are also frequently used on smartphones, using the device's sensors, such as a gyroscope and accelerometer (Zaki et al. 2020b) (Győrbíró et al. 2009). This perspective can present an imprint on the recognition of the activity. Thus, this work proposes applying AI classification in a mobile device with data collected by externally distributed sensors, which have greater precision than single sensors such as smartphones.

3. Proposed System

In this section, we present the development of the proposed work. We discuss the requirements for the construction of the mobile application and the development of a prototype containing the virtual twin and an interface.

3.1. System Requirements

Before proposing the application, we must recognize the requirements for its functioning. We performed this evaluation by inspecting the necessary system features to complete all the proposed tasks. The specific requirements to develop the proposed application are:

- User-friendly computer interface design.

- Definition of minimum hardware requirements for the application to work.
- Construction of the virtual twin replicating the user's movements and interface representing the type of movement.
- Development of the history functionality, where the path traveled on the map, and the replication of the movement will be presented.
- Statistics presentation screen, containing quantitative data on each activity performed.

3.2. Overview of the Proposed System

The proposed system has three main modules, and the first one is a wearable device. This device is a pair of pants containing a set of sensors responsible for collecting data at four different points. This data works as the baseline for the prediction algorithm.

The second module is an application and data management server. The produced data is submitted to an AI model that returns the result of the classification of the user's movement. This model classifies the movement performed into three classes: stopped, walking, or running.

The third module is the mobile application, which captures the data sent by the server and replicates the movement performed on the virtual twin, in addition to showing the movement type classification and other data, such as activity history and statistics. The application's back end also has a database for storing sensor and application information. Figure 2 displays the dataflow diagram for the proposed system.

For this work, the wearable device and the AI movement classification are fully operational, while the mobile application is still in development. The prototypes of the mobile application will be presented below.

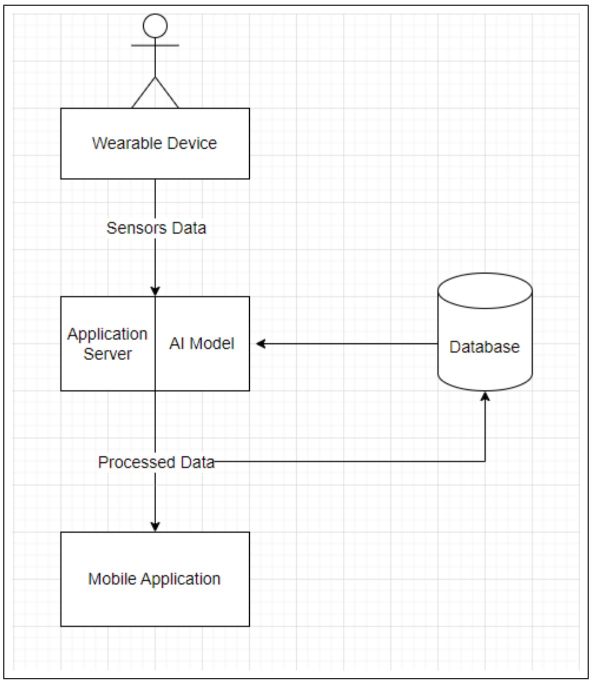

Figure 2. System diagram.

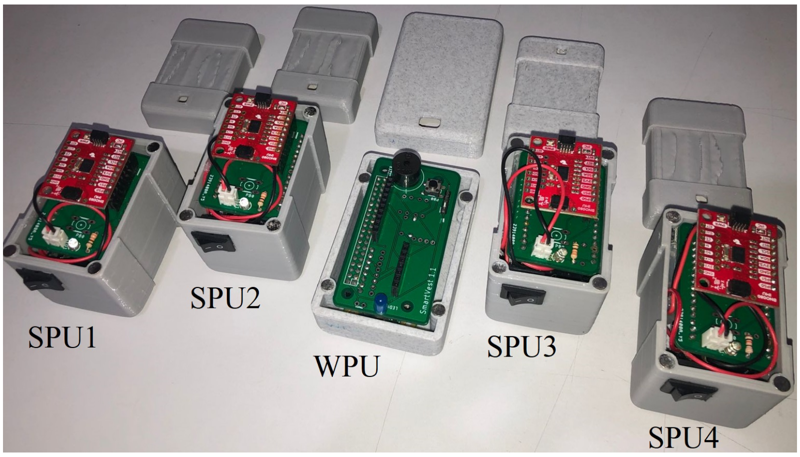

Figure 3. Wearable device used to collect individual's movement data.

3.3. Wearable sensors to collect data

Figure 3 presents a wearable device that has a center called WPU for data pre-processing and four sensors (SPUs) responsible for capturing and sending data to the WPU. The SPUs have a set of state-of-the-art IMUs (Inertial Measurement Units) to collect the physical movement of the user's leg. Figure 4 shows the position locally in the human body to collect data.

Sensor Processing Unit – SPU

The SPUs are incorporated by the sensors with the following hardware in Table 1:

Table 1. SPU hardware description

Component	Description
BNO080 IMU	9-degree inertial sensor comprising accelerometer, gyroscope, and magnetometer readings.
Li-ion battery	power source for the device.
NodeMCU ESP-32	Hardware platform based on Espressif ESP-32 solution.

Wearable Processing Unit – WPU

The WPU will receive the data collected by the SPUs, storing it for later analysis in the mobile application. This topology allows the sensors to preserve their limited energy, while the pre-processing and data transmission are centralized, reducing the possibility of errors and centralizing the server connection only with the WPU. The WPU incorporates the following hardware:

- **Humidity and temperature sensors;**
- **Raspberry Pi Zero W;**
- **BNO080 IMU.**

Robustness requirements are essential for constructing these devices, such as weight and size (Niu et al. 2018). As the sensors developed are made of lightweight components, they are comfortable for users, allowing free movement to carry out activities. Considering that the wearable device produced is a prototype, its dimensions were based on the minimum possible space to accommodate all the hardware. Thus, the challenge of reducing the size of the device would be the manufacturing of a specific modularized hardware.

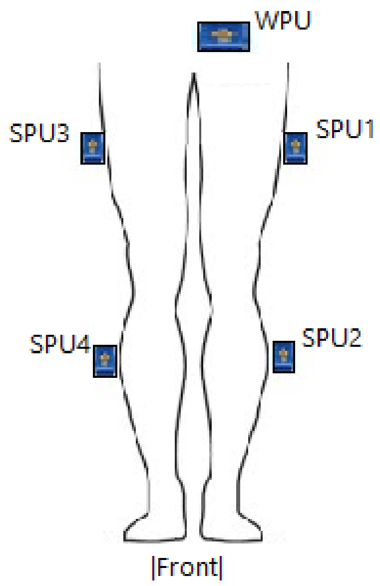

Figure 4. Wearable device positions.

3.4. AI Module

The AI algorithm for classifying the wearable device data uses LSTM (Long short-term memory) recurrent neural networks (RNN)(Hochreiter and Schmidhuber 1997). These deep learning networks are commonly used to learn about events by time series analysis like HAR (Mekruksavanich and Jitpattanakul 2021).

As a human activity, such as walking, depends on information over time, this method becomes appropriate in this context. Thus, the data processed by the WPU can be classified and sent to the mobile app to present the digital gem of the predicted activity.

Was developed a deep learning model with LSTM using a sliding window length of 10 and a step of 2. The model showed improved precision within this smaller interval. It consisted of a bidirectional layer, a Flatten layer, a Dense layer with Relu activation, a dropout layer, and a final Dense layer with softmax activation. Considering the size of the data, the system was trained for 20 epochs. For the evaluation of the algorithm, we used the standard evaluation metrics, Precision, Recall, and F1-Score (Hossin and Sulaiman 2015). Precision (equation 1), shows the data classified as really belonging to a class, true positive, Recall (equation 2), makes a system evaluation to find the positive samples of the set, and F1 - score (equation 3), the weighted harmonic mean between precision and Recall.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

True positives (TP) are data correctly classified by the model. True negatives (TN) represent the same as the negative class. The false positive (FP) refers to the result classified incorrectly for the positive class, and the false negative (FN) incorrectly for the negative category. Finally, the confusion matrix is also applied to show the visualization of the distribution of correct and incorrect classifications of each class.

3.4.1. The Dataset

The data used (dat 2022) to present the digital twins in the mobile app, the training AI model was collected and pre-processed by a wearable solution attached to the lower part of the user's body. This dataset was developed by collecting data from four SPUs placed on the user's legs to recognize walking activities. To capture the data, the device was placed on the same individual for the entire data capture process in order to ensure data homogeneity. This capture was also conducted at a normalized rate, meaning that it had a constant sampling frequency of 50Hz, which was determined to be suitable for modeling human activities (Ravi et al. 2005). The dataset has information from each of the SPUs, Q-I, Q-J, Q-k, and Q-R, corresponding to the I, J, K, and R quaternions, respectively, each sensor.

3.4.2. System interfaces and functionalities

We employed the Unity framework in developing the mobile application. This tool is an engine for creating games that allow the creation and control of virtual characters easily and intuitively, in addition to providing several tools for interface design. We developed a 3D character and a test scenario for the presented prototype. Figure 5 displays the application's main screen.

The digital twin behaves according to the user's movement, representing an abstraction of the measurements provided by the model. The data will be passed from the sensors to the server, which will save them in the database with the time and the route of the user captured by GPS. The same data will be passed to the application, which will map the movement in the virtual twin's body to replicate the movement, while the AI module classifies the movement and presents the result in the "Movement Type" field, being able to obtain values standing, walking or running.

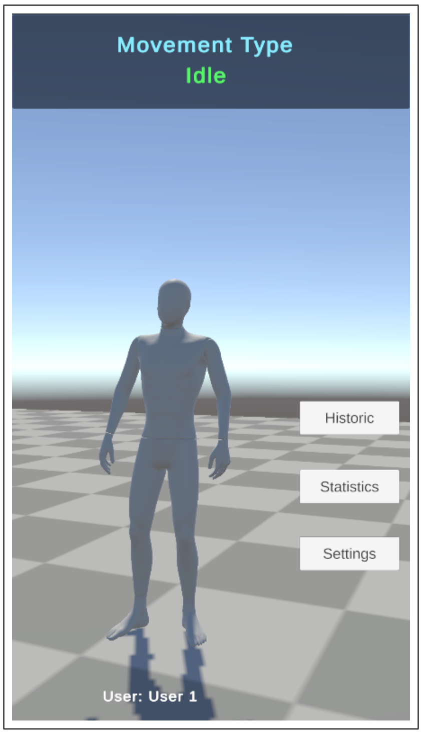

Figure 5. Virtual twin and UI prototype.

One of the major challenges in developing a virtual twin application to represent human motion is the synchronization of real and virtual movement. Sensor data must be processed to eliminate anomalies caused by sensor errors or capture issues. Connection problems can also interfere with the representation of motion due to packet loss during data transmission. Another important aspect is the normalization of sensor data to match the values used in Unity, as these values may have scale differences. To overcome this problem, a capture of generic data representing walking and running movements will be performed using the virtual twin, and then compared with the real sensor data.

Another critical part of the application will be the user history containing a chronological representation of the captured data. To store the captured data, MongoDB was chosen as the database due to its characteristics such as high performance, flexibility in data structure, and horizontal scalability. On this screen, it will be possible to see the path taken by the user represented on a map using the GPS data retrieved by the application. It will also be possible to visualize the movement performed by the user along the way, represented by the virtual twin and the classification of the movement.

Finally, the application will also allow the user to collect statistics containing quantitative data such as the time spent performing a specific activity (walking or running), the distance covered by the user according to the type of movement, and the time spent on the activity. These statistics are presented through values and graphs.

Another feature is the configuration of specific parameters of the application. For instance, the user can choose the number of days to store historical data and clean it, the accuracy of movement classification, and the status of sensors.

So far, only the 3D character of the virtual twin and the interface have been developed. It is possible to pass the sensor values to the character's vectors in order to perform the movement, but it is necessary to process the data in order to generate a real representation of the movement. The other features are still being developed.

4. Results and Opportunities

In this work, we have the preliminary results of the system, with the results of the data collected by the sensors and trained by the AI model. We also present some challenges from the point of view of app development, and the experiences gained through development are presented in this section as lessons learned.

The system with the AI model - The data collected by the WPU was trained offline by an AI algorithm for the classification of four classes: seated, stand, walk, and iwuphill. With these use cases, we evaluated the AI models to standard metrics. For each class, we evaluated the precision, recall, and F1-score. We also evaluate the global average for each case. Thus, the data training process using an LSTM model proved adequate.

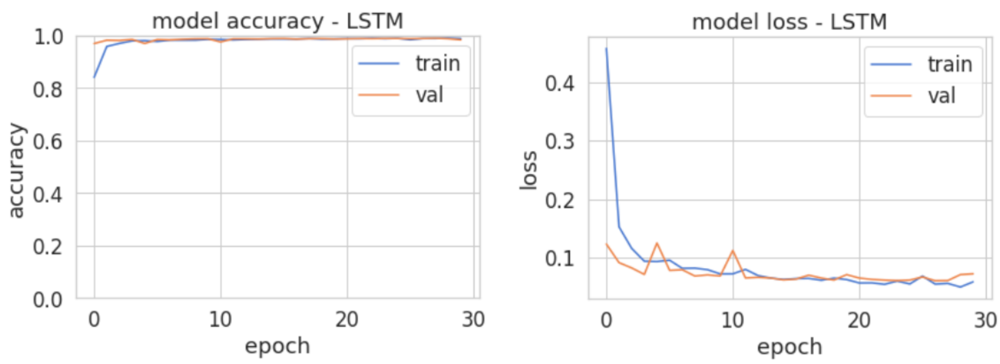

Figure 6. Evaluation of the accuracy and loss values for the training and validation sets.

Figure 6 shows the results of training the LSTM model. The graphs show a zero trend in each epoch. This means that there was no overfitting in training, with satisfactory convergence for the AI model. Table 2 displays the metrics for the LSTM.

Table 2. Metrics for the LSTM model

	Precision	Recall	F1-Score	Support
seated	1.00	1.00	1.00	396
stand	0.99	1.00	0.99	1089
walk	0.99	0.97	0.98	916
iwuphill	0.96	0.98	0.97	747
Macro average	0.98	0.99	0.99	3148
Weighted average	0.98	0.98	0.98	3148
Global Accuracy:	98%			

Figure 7 displays the test results for the AI model. In this test, we see that the model has accurately classified the data into the four classes in the dataset. The results indicate that the LSTM model can efficiently classify the data collected by the sensors.

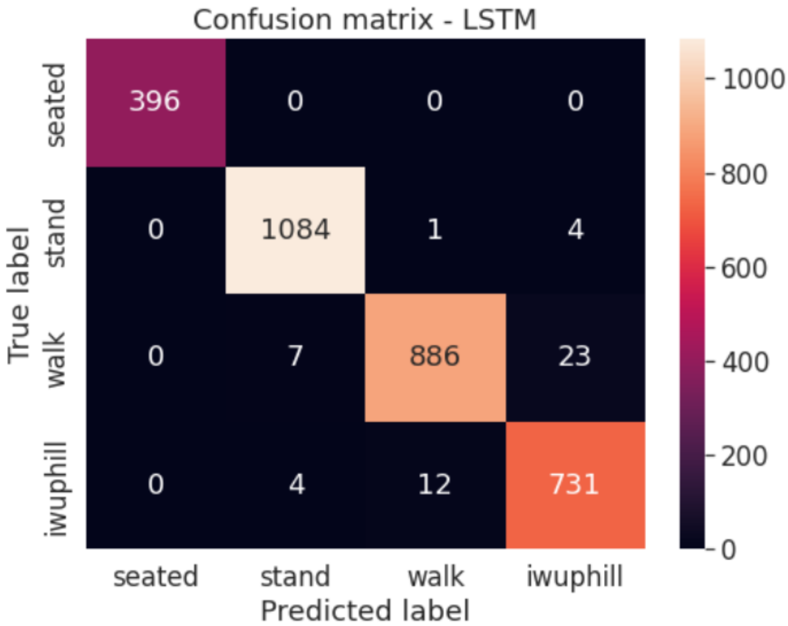

Figure 7. Confusion Matrix

Opportunities for integrating the app with the system - One of the main benefits of this type of application is the possibility of improving the user's decision-making model through the information provided by the app. For example, the system can present to the individual the activity performed on the interface of a mobile device. This information presented brings a gain for this purpose since the graphical representation reinforces the classification made by the AI model.

A system that represents real-world data in a virtual twin synchronously and accurately allows the representation of different types of movement and also the study of user biomechanics for orthopedic or sports performance purposes. The validation of the required data types for accurate representation, along with the necessary technologies for the proper functioning of the system as a whole, is also of great importance. Taking into account the connection technologies used for data exchange, the type of device utilized, and its resources such as available sensors, processing speed, and memory capacity.

5. Conclusion and Future work

This work presents a system with a wearable device integrated with an AI application for walking and running activities. In the first sections of the work, we study the main aspects related to constructing this system. We understood and proposed an AI application solution for wearable devices. Since walking and running sports are some of the most popular physical activities performed worldwide, we propose a system that uses wearable sensors to recognize this user activities. When performing data fusion, the AI algorithm showed an overall accuracy of 98%. This result indicates that the device can be applied to other case studies, for example, helping athletes improve performance in training and providing precious information about their movements in real-time.

In future works, we can train the AI model to recognize other movements, such as jumps, squats, and kicks. Such data could be used to develop specific applications for sports such as football, bodybuilding, and athletics. Another area that one can explore is the metaverse. It would be possible to replicate the movement of the characters precisely to perform the activities in a game using the proposed system.

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References

(2022). Dataset for human activity recognition har. `https://www.kaggle.com/datasets/jonathansilva2020/dataset-for-human-activity-recognition-har`.

Ann, O. C. and Theng, L. B. (2014). Human activity recognition: a review. In *2014 IEEE international conference on control system, computing and engineering (ICCSCE 2014)*, pages 389–393. IEEE.

Borowski-Beszta, M. and Polasik, M. (2020). Wearable devices: new quality in sports and finance. *Journal of Physical Education and Sport*, 20:1077–1084.

Cosoli, G., Antognoli, L., Veroli, V., and Scalise, L. (2022). Accuracy and precision of wearable devices for real-time monitoring of swimming athletes. *Sensors*, 22(13):4726.

Demrozi, F., Pravadelli, G., Bihorac, A., and Rashidi, P. (2020). Human activity recognition using inertial, physiological and environmental sensors: A comprehensive survey. *IEEE Access*, 8:210816–210836.

Győrbíró, N., Fábián, Á., and Hományi, G. (2009). An activity recognition system for mobile phones. *Mobile Networks and Applications*, 14(1):82–91.

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, 9(8):1735–1780.

Hossin, M. and Sulaiman, M. N. (2015). A review on evaluation metrics for data classification evaluations. *International journal of data mining & knowledge management process*, 5(2):1.

Lara, D. and Labrador, M. A. (2012). A mobile platform for real-time human activity recognition. In *2012 IEEE Consumer Communications and Networking Conference (CCNC)*, pages 667–671.

Lee, S., Park, M., Lee, K., and Lee, J. (2019). Scalable muscle-actuated human simulation and control. *ACM Transactions On Graphics (TOG)*, 38(4):1–13.

Lu, T.-W. and Chang, C.-F. (2012). Biomechanics of human movement and its clinical applications. *The Kaohsiung journal of medical sciences*, 28(2):S13–S25.

Mekruksavanich, S. and Jitpattanakul, A. (2021). Biometric user identification based on human activity recognition using wearable sensors: An experiment using deep learning models. *Electronics*, 10(3).

Niu, L., Han, Q., Wang, T., and Quan, G. (2018). Reliability-aware energy management for embedded real-time systems with (m, k)-hard timing constraint. *Journal of Signal Processing Systems*, 90:515–536.

Ravi, N., Dandekar, N., Mysore, P., and Littman, M. L. (2005). Activity recognition from accelerometer data. In *Aaai*, volume 5, pages 1541–1546. Pittsburgh, PA.

Schiewe, A., Krekhov, A., Kerber, F., Daiber, F., and Krüger, J. (2020). A study on real-time visualizations during sports activities on smartwatches. In *19th International Conference on Mobile and Ubiquitous Multimedia*, pages 18–31.

Taghavi, S., Davari, F., Malazi, H. T., and Abin, A. A. (2019). Tennis stroke detection using inertial data of a smartwatch. In *2019 9th International Conference on Computer and Knowledge Engineering (ICCKE)*, pages 466–474. IEEE.

Wang, P., Liu, H., Wang, L., and Gao, R. X. (2018). Deep learning-based human motion recognition for predictive context-aware human-robot collaboration. *CIRP Annals*, 67(1):17–20.

Xu, Y. and Qiu, T. T. (2021). Human activity recognition and embedded application based on convolutional neural network. *Journal of Artificial Intelligence and Technology*, 1(1):51–60.

Zaki, T. H. M., Sahrim, M., Jamaludin, J., Balakrishnan, S. R., Asbulah, L. H., and Hussin, F. S. (2020a). The study of drunken abnormal human gait recognition using accelerometer and gyroscope sensors in mobile application. In *2020 16th IEEE International Colloquium on Signal Processing Its Applications (CSPA)*, pages 151–156.

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Zhuang, Z. and Xue, Y. (2019). Sport-related human activity detection and recognition using a smartwatch. *Sensors*, 19(22):5001.