The Power of Gyroscope Data: Advancing Human Movement Analysis for Walking and Running Activities

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Abstract: The ability to faithfully reproduce the real world in the virtual environment is crucial to provide immersive and accurate experiences, opening doors to significant innovations in areas such as simulations, training, and data analysis. In such a way that actions in the virtual environment can be applied, which would be challenging in the real world due to issues of danger, complexity, or feasibility, enabling the study of these actions without compromising these principles. Additionally, it is possible to capture real-world data and analyze it in the virtual environment, faithfully reproducing real actions in the virtual realm to study their implications. However, the volatility of real-world data and the accurate capture and interpretation of such data pose significant challenges in this field. Thus, we present a system for real data capture aiming to virtually reproduce and classify walking and running activities. By using gyroscope data to capture the rotation of axes in the lower human limbs movement, it becomes possible to precisely replicate the motion of these body parts in the virtual environment, enabling detailed analyses of the biomechanics of such activities. In our observations, in contrast to quaternion data that may have different scales and applications depending on the technology used to create the virtual environment, gyroscope data has universal values that can be employed in various contexts. Our results demonstrate that, by using specific devices such as sensors instead of generic devices like smartwatches, we can capture more accurate and localized data. This allows for a granular and precise analysis of movement in each limb, in addition to its reproduction. This system can serve as a starting point for the development of more precise and optimized devices for different types of human data capture and analysis. Furthermore, it proposes creating a communication interface between the real and virtual worlds, aiming to accurately reproduce an environment in the other. This facilitates data for in-depth studies on the biomechanics of movement in areas such as sports and orthopedics.

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 and how they affect movement, it is also possible to act preventive against such injuries and corrective help in healing and rehabilitation (Lu and Chang(2012)). Deepening knowledge of the human body movement is also of great importance 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.

The gyroscope data captured by sensors can be a significant source of information not only for the

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precise reproduction of movement in the digital twin but also for detecting anomalies related to gait assessment. Such evaluations are primarily carried out through visual observation by a medical professional, which can be imprecise and involve highly subjective rating scales, underscoring the importance of digital technologies as valuable tools for capturing objective data and information for accurate diagnosis (Celik et al.(2021)).

Using SPUs directly connected to the mobile device (smartphone) instead of consolidating the data in a WPU, as proposed in (Alvim et al.(2023)), can help improve the speed at which information reaches the device for representation in the virtual twin. Employing a device like WPU to mediate communication may increase the delay of information, besides being another critical element of the system, susceptible to errors and communication issues.

This paper presents a mobile application to capture and recognize 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.

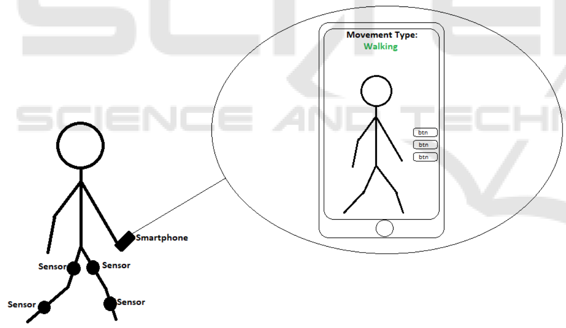


Figure 1: Application usage representation.

The main contribution of this work is:

- A proposal for a mobile platform composed of an integrated hardware and software solution for reproducing real movements by data sent from a new wearable device using AI for human 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 literature, 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 human walking, tools and mobile apps in activity recognition with intelligent devices.

2.1 Human Gait

The ability to walk is crucial for human life, representing one of the primary means of moving from one place to another in the environment. This movement is meticulously coordinated among the different segments of the body, involving a complex interaction between internal and external factors. Controlled by the neuromuscular and skeletal system, walking is traditionally defined based on patterns of foot contact with the ground and biomechanical properties (Mirelman et al.(2018)).

The gait cycle comprises two events, from the moment one foot makes contact with the ground until that same foot touches the ground again. The limbs undergo a support phase where the foot is in contact with the ground, and a swing phase when the foot is not in contact with the ground. The support phase, representing 60% of the movement, can be subdivided into five subphases, and the swing phase, representing 40% of the movement, into three subphases (Bonnefoy-Mazure and Armand(2015)).

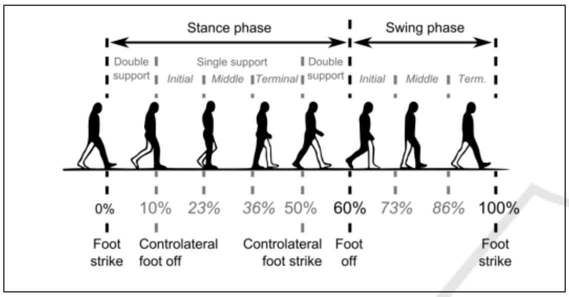


Figure 2: Gait cycle phases and subdivisions (Bonnefoy-Mazure and Armand(2015)).

The center of gravity of the human body is the point where all the body's mass is considered to be concentrated. It is a simplified representation of the midpoint concerning the total body weight (Yiou et al.(2017)). During gait, it is crucial to maintain the center of gravity (CG) of the body within the base of support to ensure stability and balance. When the CG moves outside of this base, imbalance occurs, increasing the risk of falls. Therefore, controlling and maintaining the stability of the CG are essential aspects for safe and efficient gait. This involves the coordinated movement of body segments to minimize any displacement of the CG that may occur during walking (Moon et al.(2022)). Reducing the energy cost of walking and maintaining movement stability are related to the kinematics of the CG. Individuals are constrained to specific movements during walking; conversely, decreased dynamic stability in the CG directly impacts energy expenditure and may render movement less stable (Tucker et al.(1998)).

The examination of kinematics delineates the movements of body segments. Given the relative complexity of the human body and its motions, modeling is essential for simplifying these mechanisms. Quantifying joint kinematics in three dimensions is paramount for comprehending and characterizing human body movements (Pacher et al.(2020)).

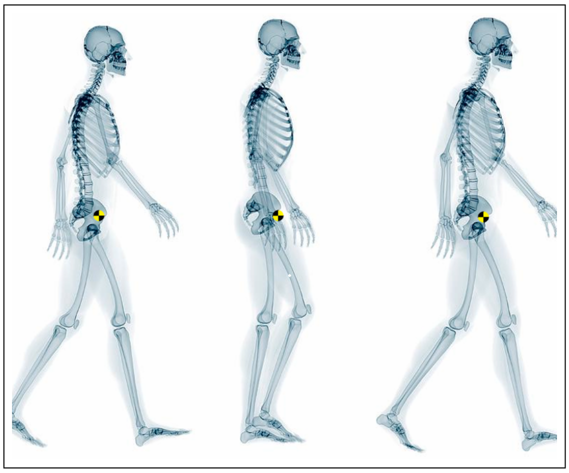


Figure 3: Representation of human body center of gravity.

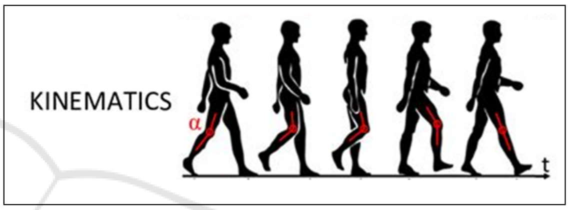


Figure 4: Representation of knee kinematics in the gait cycle.

2.2 AI Tools Applications in Human Recognition

Advances in gait analysis with machine learning are changing how we understand biomechanical systems. After picking the best technique, the model is trained and checked using the training set to see how well it works. Then, its performance is tested with the test set. If it's accurate enough, we're done; otherwise, we adjust the model and keep training until we reach the desired accuracy. Focusing on making the system less complex, careful feature selection is key (Khera and Kumar(2020)).

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 the usage of friendly visual interfaces, they form promising solutions for constructing a new system (Demrozi et al.(2020); Ann and Theng(2014)).

Authors use embedded devices with convolutional neural networks (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.

2.3 Mobile Applications and Wearables

Wearable technology, utilizing accelerometers, gyroscopes, and magnetometers, provides a means to measure a combination of gait variables. These devices have gained popularity due to their ease of use and affordability. Wearable devices offer the ability to measure various aspects of gait during running in different environments, which can contribute to our understanding of running performance, fatigue, and injury mechanismsd (Mason et al.(2023)).

Most studies involving sensor usage utilize models called inertial measurement units (IMU). These units are generally equipped with accelerometers and gyroscopes, and some models also include magnetometers. By using gyroscope data, it is possible to achieve easier reproduction due to the lack of translation requirement, as the angular velocity at any position of the body remains the same. They also suffer from less noise unlike accelerometers (Prasanth et al.(2021)).

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. Also, we present the interface design and the AI module.

3.1 System Requirements

Before proposing the application, we must recognize the requirements for this functioning. We performed this evaluation by inspecting the necessary system features to perform 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 consists of three modules: the wearable device containing sensors, the mobile application, and the application server. The wearable device comprises four sensors positioned on the user's legs which are responsible for data collection from user actions, this data works as the baseline for the prediction algorithm. The collected data is subsequently sent to the mobile application, which forwards the data to the application server and replicates the movements in the digital twin. The server is responsible for storing the data in the database and classifying the movement using artificial intelligence. Figure 5 displays the dataflow diagram for the proposed system.

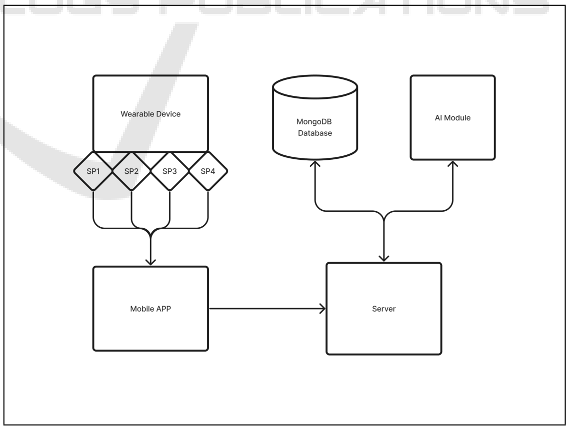


Figure 5: System diagram.

3.2.1 Wearable Device and Sensors

Figure 6 represents the sensors (SPUs) used to capture the user action data. 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 7 shows the position locally in the human body to collect data.

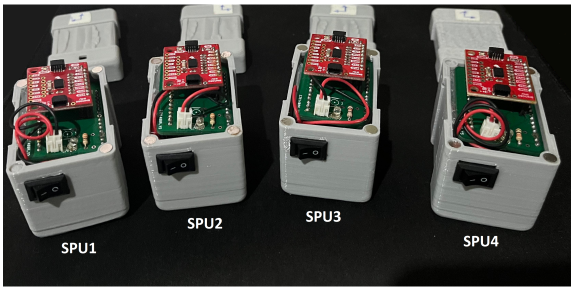


Figure 6: Wearable device used to collect individual's movement data.

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.

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.

Sensors can capture data from accelerometer, gyroscope, and magnetometer, in addition to quaternions. For the representation of motion in the virtual twin, we will use gyroscope data comprising values for the X, Y, and Z vectors. When the sensor rotates on any of these vectors, it returns a positive or negative value related to the angle the sensor has been rotated. The data transmission rate of the gyroscope for each SPU is around 50 ms, representing 20 samples per second, allowing us to accurately replicate user movements in the virtual twin. A low data update rate is important because higher values can cause desynchronization in the representation of virtual twin movements. This problem can also occur if there is a failure in data transmission due to interference or the drop of any SPU; the user's movement may have changed while the data was not sent, causing the virtual twin to become desynchronized.

Each sensor was configured to send data every 50 milliseconds via Bluetooth connection, allowing for the transmission of 20 samples per fraction of a second. Combining the data from the 4 sensors results in a total of 80 data samples per second. Considering floating-point values of 4 bytes each for the three axes, we have a total of 12 bytes per sensor reading. Multiplying this by the 4 sensors and 80 samples, we achieve a rate of 960 bytes per second, a value well below the total capacity of a Bluetooth connection, providing sufficient margin for complete data transmission.

Another crucial aspect is the alignment of the rotation axis values with those used in the virtual twin. On the sensor hardware board, there are guidelines for the positioning of the X, Y, and Z axes, and if the board is oriented differently, it is necessary to adjust the values to correctly relate the data.

In the current state, both the hardware and its embedded software are fully developed, making it possible to capture all types of data mentioned earlier and transmit them via Bluetooth.

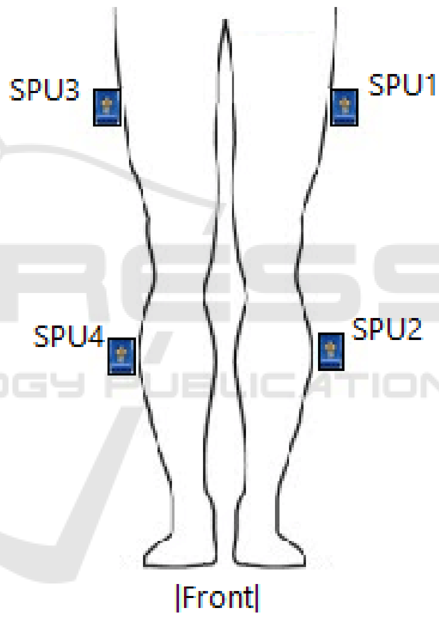
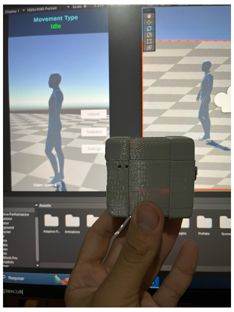
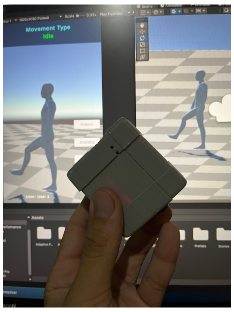


Figure 7: Wearable device positions.

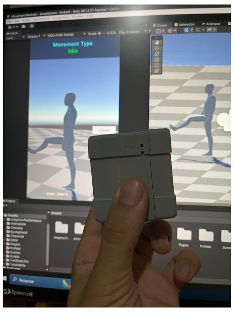
The System - In the development of the system, the interface and the virtual twin proved to be highly responsive. By integrating gyroscope values into the avatar's control variables, we were able to precisely control the rotation axes of its legs. Initially, the feasibility of using quaternions to replicate user movement in the virtual twin was tested. However, despite Unity accepting the insertion of these values for object modification, it was observed that when directly applied to the avatar, it did not respond correctly to user movements. On the other hand, the use of gyroscope data allowed for an exact reproduction of the device's movement in the virtual object, as shown in the images below.



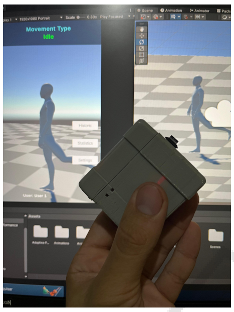
(a) Sensor on 0° rotation.



(b) Sensor on 45° rotation.



(c) Sensor on 90° rotation.



(d) Sensor on -45° rotation.

Figure 8.

3.2.2 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 9 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.

Another critical part of the application will be the user history containing a chronological representation of the captured data. 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.

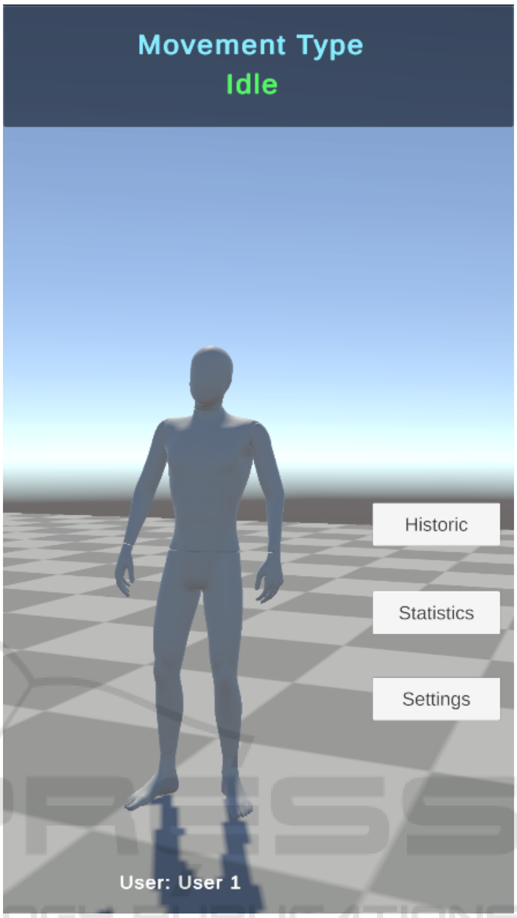


Figure 9: Virtual twin and UI prototype.

Finally, the application will also allow the user to collect statistics containing quantitative data such as the time spent performing a specific activity (standing, 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.

3.3 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 can be classified and sent to the mobile app to present the digital gem of the predicted activity.

For the evaluation of the algorithm, we used the standard evaluation metrics, Precision, Recall, and F1-Score (Hossin and Sulaiman(2015)). Precision 1, shows the data classified as really belonging to a class, true positive, Recall 2, makes a system evaluation to find the positive samples of the set, and F1 - score 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.

3.3.1 The Dataset

The data used (dat(2024)) to create digital twins in the mobile application and to train the artificial intelligence model were captured and processed through a wearable solution attached to the lower part of the user's body. This dataset was obtained by collecting information from gyroscopes located on the user's legs, which record movements along the X, Y, and Z axes. Additionally, the data includes the sensor identifier and the timestamp at which the record was captured. These data were collected with the aim of recognizing standing and walking activities. The dataset contains information from each gyroscope, specifically along the X, Y, and Z axes, representing the movements along these axes for each sensor.

For preliminary testing purposes of the AI model, only data and classification of standing and walking events were performed to validate training, prediction, and classification, as well as data augmentation on the data generated in sensor capture. The next step is to collect more data related to these events, and also to capture data related to the running event, which is slightly more complex due to the user's speed and the stability required in the sensors to accurately capture the data.

4 RESULTS AND OPPORTUNITIES

This paper presents the initial findings of the system, showcasing outcomes derived from the data acquired through sensors and processed by the AI model. Additionally, we outline various challenges encountered in application development and share insights gained throughout the development process as valuable learning experiences in this segment.

The AI Model - We trained an AI system offline with the data we collected. The system learned to classify two main activities: standing and walking. We assessed its performance using standard measures like precision, recall, and F1-score for each activity, as well as an overall average. The training process using an LSTM model proved effective.

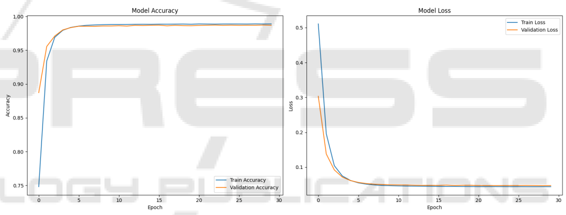


Figure 10: Evaluation of the accuracy and loss values for the training and validation sets.

The results of training the LSTM model are depicted in the figure 10. The graphs display a consistent trend of convergence throughout each epoch, indicating minimal deviation from the desired outcome. This observation suggests that the model's performance was stable during the training process, with no evidence of overfitting. Overall, the convergence pattern reflects satisfactory progress in optimizing the AI model for the intended task. Table 2 displays the metrics for the LSTM.

Table 2: Metrics for the LSTM model.

	Precision	**Recall**	**F1-Score**	**Support**
stand	0.98	1.00	0.99	4851
walk	0.99	0.97	0.98	2696
Macro average	0.99	0.98	0.99	7547
Weighted average	0.99	0.99	0.99	7547
Global Accuracy:	99%			

The Figure 11 displays the test results for the AI model. In this test, we observe that the model accurately classified the data into the two classes in the dataset. The results indicate that the LSTM model can efficiently classify the sensor data.

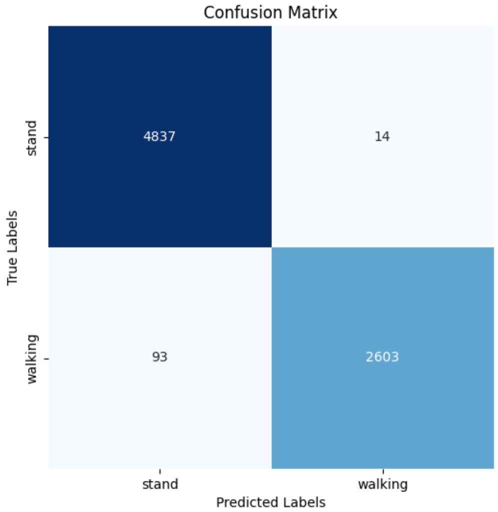


Figure 11: Confusion Matrix.

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.

5 CONCLUSION AND FUTURE WORK

In this work, we introduced an innovative system for real data capture aiming to virtually reproduce and classify walking and running activities. We utilized gyroscope data to capture the rotation of axes in lower human limbs' movements, enabling a precise replication of these body parts' motions in the virtual environment. Our results indicate that, by employing specific devices such as sensors instead of generic devices like smartwatches, more accurate and localized data can be captured. This allows for a granular and precise analysis of movement in each limb, in addition to faithful reproduction.

The main contribution of this work includes proposing a mobile platform consisting of an integrated hardware and software solution for reproducing real movements. We demonstrated that utilizing gyroscope data, with universal values, provides a more consistent approach compared to quaternion data. Furthermore, we discussed the significance of applying this technology in the orthopedic and sports field, emphasizing the relevance of studying human movement to understand anatomical factors influencing movement mechanics. The proposed system serves as a starting point for developing more precise and optimized devices for various types of human data capture and analysis.

As future work, we highlight several promising directions for the continuation of this research. Firstly, we aim to further enhance the system by exploring different machine learning techniques and AI algorithms for activity classification. Additionally, we plan to broaden the system's scope to include a wider variety of physical activities, allowing for a more comprehensive application in different contexts.

Integrating more sensors and optimizing the hardware are crucial considerations to improve the system's accuracy and effectiveness. We also intend to implement a more robust communication interface between the real and virtual worlds, enabling an even more precise reproduction of the environment in which activities are being performed.

Moreover, collecting data in real-world scenarios with a more diverse sample can enhance the generalization of the AI model, making it more robust across different contexts and for various users. Finally, we contemplate expanding the system to practical applications, such as health monitoring and personalized training, to maximize its impact on human well-being.

These future directions aim to refine the application and effectiveness of the proposed system, enabling significant advancements in the fields of biomechanics, health, and physical training within the realm of computer science.

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