AI-based Personalized Human Activity Recognition in Walking and Trekking Sports: A Case Study

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***Abstract*—Human Activity Recognition (HAR) is a topic of interest in several areas, for example, health and sports. There are several ways to perform HAR tasks, which must be understood before creating the desired tools. In this article, we carry out a theoretical study to understand the HAR problem and its main techniques using AI. In addition, we present a case study in which we developed a prototype HAR system for walking and trekking. In this study, we evaluated new hardware for HAR with IMUs with 9 degrees of freedom. This system, composed of four sensors called SPU's was attached to the user's lower limbs. A device called WPU collects information from these sensors. With the fusion of the collected data, AI techniques were applied with CNN models reaching an accuracy of 98% to classify the human activities in this context, thus creating new perspectives for using AI to HAR in sports.**

***Index Terms*—HAR, SPU, WPU, AI, device.**

I. Introduction

Performance evaluation in sports is an important asset at amateur and professional levels [1]. Additionally, performance measurement has a broad impact on economic decisions related to sports practice [2]. Thus, novel developments in performance analysis tools are a topic of interest.

New technology to monitor performance is a topic of research and development in several amateur sports, such as athletics tests [3], among others. These works display the potential to understand performance in amateur sports through novel hardware and software technology. There is a developing interest in upcoming novel solutions towards this goal.

There is extensive interest in measuring human activities using wearable computing. Ramanujam et al. [4] used traditional feature extraction methods and deep learning models to HAR. This combination creates a promising scenario for the development of novel solutions.

In this work, we explore the theoretical and practical aspects of HAR; specifically, we target its usage for walking and trekking. Figure 1-a shows the solution proposes to monitor the users' activities through wearable sensors, and Figure 1-b the data processing to develop an AI model. Also, we present multiple sensors attached to the user's lower limbs that continuously collect information through IMUs and send it to a raspberry pi zero W. An AI algorithm classifies this data according to the activity performed in this scenario.

II. Theoretical References and Related Work

This section provides a comprehensive theoretical approach to the HAR issue. We display its fundamentals, main techniques, and how it relates to sports. Also, we present the results of some literature reviews with an overview in this context.

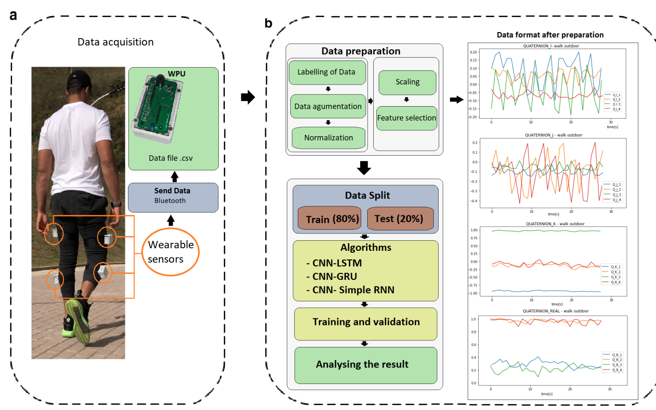

Fig. 1. Actual usage with wearable device.

A. Human Activity Recognition (HAR)

HAR is computationally perceiving human behavior. Vrigkas et al. [5] state that human activities can be divided into gestures, atomic actions, interactions, group actions, behaviors, and events. These authors also state that human activities can be classified as unimodal or multimodal.

In unimodal characterization, all gathered data corresponds to the same sensor modality (images, audio, etc.). Also, these techniques are usually based on optical flow or sensor time series, as our solution in the second part is guided. Unimodal HAR is divided between *space-time*, *stochastic*, *rule-based*, and *shape-based* methods. In contrast, multimodal recognition employs data from different modalities to perform the recognition task. Multimodal HAR is usually divided between *affective*, *behavioral*, and *social networking* methods.

B. Vision-based HAR

Vision-based HAR has become a hot topic in the [6] computer vision field. This set of techniques can be divided into two main areas: contact-based and remote methods. Contact-based techniques require physical contact with the [6] acquisition device. The authors estimate that most developed solutions are remote, mainly in more recent applications.

There are some applications in this scenario. Bijalwan et al. [7] used vision-based HAR to analyze and restore human gait deformity and postural instability. However, the data collected by the Microsoft Kinect V2 can present difficulties in external environments, mainly for classifying information in real-time.

C. Sensor-based HAR

Chen et al. [8] state that novel sensor devices and the wider Internet of Things have enabled the creation of novel HAR solutions. They state several issues in sensor-based HAR, including annotation scarcity, class imbalance, computational cost, and privacy. Additionally, they state that deep learning has a meaningful role in developing solutions, especially using convolutional neural networks (CNNs) and recurrent neural networks (RNNs).

A sensor-based approach adds mobility, unobtrusiveness, and ease of usability, as stated by Nweke et al. [9]. They also enforce the importance of deep learning techniques, which can perform an automatic feature extraction step rather than a manual step. They state that several methods apply within this context and divide them into generative, discriminative, and hybrid modes.

There are several applications for sensor-based HAR. For instance, it can be used to classify activities for daily living (ADLs) [10], sports [11], among others. Several works in this area indicate its relevance to the given context.

D. AI-based HAR

AI is a central topic in the development of novel HAR solutions. Dua, Nidhi, et al [12] [13] show the influence of deep models to create new solutions in this scenario. This discussion starts by returning to Chen et al. [8], where they display that deep learning has an important tool for developing novel HAR solutions. They also stated that some of the main models used in HAR applications are recurrent neural networks and convolutional neural networks. Several applications employ these techniques for the creation of novel solutions.

Ramasamy et al. [14] assert that these activities start with the premise of extracting knowledge from raw data. They affirm that using raw data in HAR is useful for functional and behavioral health monitoring, fitness tracking, and sports analytics. In their work, the authors display that several initiatives have created datasets containing samples from human activities. They also enforce some of the popular deep learning models in appliances are deep neural networks (DNNs), CNNs, and recurrent neural networks (RNNs), including long short-term memory (LSTM).

Several authors employ these techniques to solve HAR tasks. Wan et al. [15] applied and compared several algorithms in the development of a smartphone-based HAR application proposal. Zhou et al. [16] assess how to create deep learning models for HAR using weakly labeled data. Bianchi et al.

E. HAR in Sports

Finally, a last crucial matter aspect in this discussion is the usage of HAR in sports. Some authors employ these technologies in the creation of sports applications. Hsu et al. [17] proposed the usage of wearable technology and AI in the development of HAR applications for sports and daily activities. Imram [18] also proposes the usage of the sensors-based and shallow convolutional network in recognition of sports activities. Steels et al. [19] enforce a similar proposal for recreational and professional badminton. In all these cases, there was a usage of wearable inertial sensors and AI to propose a solution.

F. Considerations

Kamal et al. [20] uses deep multi-model fusion for HAR. However, this approach is unfeasible when applied in walking activities because in an external environment, the data are not well controlled, and wearable sensors are more indicated on the user's body. Thus, it allows the recognition of the activity with greater precision and detects easely inconsistencys in the gait for the prevention of injuries.

Bijalwan et al. [21] uses data fusion from Microsoft Kinect V2 and IMUs (Inertial Measurement Units) sensors. Still, this sensor hasn't the precision and accuracy of the BNO080, a 9DoF (9 Degrees of Freedom) IMU sensor. In addition, four BNO080 can more accurately detect any inconsistency in the gait performed by different users.

Sandro et al. [22] proposed deep streaming for HAR from sensors with patient data in the health area. Despite some similarities with our work, they differ in the way of delivering the information. Our work performs the analysis with an edge device, avoiding latency problems for the user when receiving data and classifying activities.

The article's contribution demonstrates that the proposed approach effectively classifies hiking and trekking using AI models. In addition, it presents complete information about the user's movements, contributing to the advancement of technology related to HAR. In the future, a possible application to monitor the physical performance of runners.

III. Context and Applicability

Today, running is one of the most popular types of physical activity performed globally [23]. Running adoption by professional or amateur athletes may be directly related to the ease of practicing this sport, as any public space can be used. The correct methodology and limb positioning instantly influence an athlete's performance. In this way, evaluating the biomechanics of the individual's body can prevent future injuries and improve their overall performance [24].

There are some solutions and devices aimed at monitoring sports activities. Some research uses cameras and body markers to assess different aspects of runners, such as gait, foot inclination angle, knee flexion, pelvic drop, running cadence, and others [25]. Despite its validity and results, the video approach to evaluate running lacks flexibility and validity since a very well-controlled environment is required. For instance, researchers frequently use recorded videos from athletes running on a treadmill as a reference to assess the previous reference points.

A. Constraints

Although being an innovative solution, the data collection environment presented by this work has some limitations. The prominent ones are listed below:

- Since many wearable sensors are used, collected data must be time synchronized through timestamps to properly capture the movement mechanics being performed; and
- Devices are powered by Lithium-ion batteries. In this way, this current setup is not able to capture a long session of exercise. For instance, short-duration sessions (5K or 10K) can be monitored. However, the solution's autonomy may, eventually, not be long enough to monitor the individual during longer courses (half-marathons or marathons).

IV. Methods

In the previous sections, the importance of the work and the main concepts in the context of HAR were presented. In this section, we present the built-in aspects of the wearable device for HAR, as well as the architecture of the system. We also discuss the environment and its constraints as a factor in understanding the design and development of the novel solution.

A. System Description

The data used for the analysis and application of the AI models are collected and pre-processed by the wearable device called WPU.This device receives data from four other sensors, with a set of high-precision IMUs, to collect the physical movement in the user's leg.

In the wearable device proposal, a Sensor Processing Unit (SPU) and a Wearable Processing Unit (WPU) were used. Figure 2 describes how the SPU and WPU sensors are attached to the user. However, the data is collected in a distributed fashion by each of the four SPUs, and then it is sent to the WPU. In the WPU, the collected data can be pre-processed and stored locally with an SD card (flash memory) or sent to an external server.

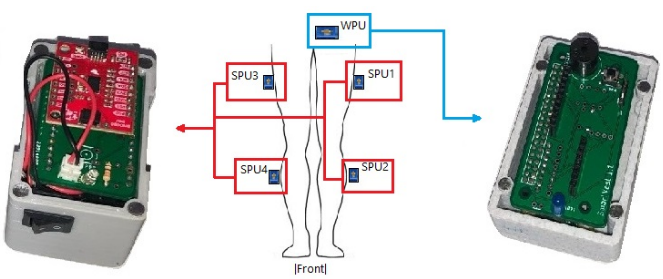

Fig. 2. Wearable device used to collect individual's movement data. Highlighted areas indicate the location where each device is positioned.

The four SPU sensors were positioned on the user's lower limbs, and the WPU on the waist. The sensors' specifications used for the prototype's construction are described in detail later.

Sensor Processing Unit – SPU

The SPUs are attached to the user's legs to collect information in real-time. Each SPU has the following constructive aspects:

- BNO080 IMU: 9-degree inertial sensor composed of accelerometer, gyroscope, and magnetometer readings. With the function of recovering the physical orientation of the user's body parts;
- NodeMCU ESP-32: Hardware platform based on the Espressif ESP-32 solution. With the function of reading the data detected by the IMU and sending them to the WPU via Bluetooth;
- Lithium-Ion Battery.

Wearable Processing Unit – WPU

The WPU consists of the following components:

- BNO080 IMU: 9-degree inertial sensor composed of accelerometer, gyroscope, and magnetometer readings. This sensor retrieves information such as temperature and humidity;
- Humidity and temperature sensors;
- Raspberry Pi Zero W.

With this, the WPU has the task of receiving data from the four SPU sensors, sequencing them - timestamp of each received packet - and: a) Storing the data locally for future analysis or b) Sending it to a remote server/service using o IEEE 802.11 Wireless Interface.

B. Dataset

As it is a prototype, data were collected by one of the authors. In the future, there is the intention to include other people in the experiment with an improved prototype version. We mount a database [26] to validate the use of the wearable device and train IA models. TableI shows the four labels in this dataset.

TABLE I
Description of Dataset Labels

Label	Description
seated	Data collected in a fixed sitting position in an ordinary chair.
stand	Data collected in the standing position.
walking	Data collected on the street with an average speed of 3km/h
wuphill	Data collected indoors, a walking activity equipment with incline and speed of 5 km/h.

We had different subphases to detect the signal illustrated in figure 1 The four SPUs are responsible for sending data to the WPU. The data received by the WPU is a composite signal with the spatial information corresponding to the quaternions, being I, J, K, REAL, and Radians. An important observation is that the data sampling frequency may be non-constant despite the four sensors having the same constructive aspects. The variation in sampling may be due to aspects of each electronic component that make up the hardware.

According to the authors [27], to model problems related to human activities, the sampling rate must be in the range of 50Hz. This means that we do not have problems with the application of AI models because we guarantee that the input data for training the algorithms are normalized. Also, for this study, the data were collected by a single user, so we can guarantee the homogeneity of the information.

The four SPUs sensors were positioned on the user's leg, as shown in Figure 2. The data collected by the WPU has four components, I, J, K, and R. Table II shows the names of these components for analysis, respectively.

TABLE II
DESCRIPTION OF THE DATA SENT BY THE SENSORS SPU

ID	Quaternion	Components
ID	Q-I	Q-I-ID
ID	Q-J	Q-J-ID
ID	Q-K	Q-K-ID
ID	Q-R	Q-R-ID

1) Dataset - Data agumentation: The data were collected by a fixed user to ensure homogeneity. The user took a break of a few days to collect new data. This ensures user recovery and data is collected as homogeneously as possible. In this context, the data collected were in low amounts. To solve the problem of the amount of data, we perform operations on the original database to increase the number of instances of each class.

Data augmentation techniques applied to the J quaternion of an instance of the walk class. This procedure was performed on all data from the original dataset. Four operations were performed on all quaternions of the four classes of the original dataset:

- **Noise**: Adds random Noise to the time series of each quaternion. The Noise added at each time point is independently and identically distributed.
- **Convolve**: Convolves time series with a kernel window.
- **Quantize**: Quantize time series for a set of levels. Values are rounded to the nearest level in the level set.
- **Drift**: Drift the time series value randomly and smoothly. The extent of Drift is controlled by the maximum Drift and the number of drift points.

We use the TSaug [28] library for data augmentation. The first operation was done with the addition of two variations, 0.1 and 0.5. The second application was the convolution operation, with a variation of 10 and 5. Third, the quantize with two variations of 10 and 20. Finally, Drift was added with four variations, max-drift=0.2 and number drift points = 5 , max-drift=0.5 and number drift points = 5, max-drift=0.3 and number drift points = 5 and max-drift=0.3 and number drift points = 3. Thus, to the dataset with data augmentation [29], we generated ten data for each data of the original dataset.

C. Evaluation Metrics

In this section, we study the options of HAR algorithms. For our context, it is interesting to have models which may have a feasible performance in the embedded environment. Thus, we evaluated three different models that solve the issue:

- Long short-term memory (LSTM): Recurrent neural networks (RNN) capable of classifying sequential, for example, temporal series, data due to their learning memory storage characteristics [30].
- Gated Recurrent Unit (GRU): Introduced by Cho et al. in 2014, GRU aims to solve the problem of gradient dissipation common in a standard recurrent neural network. The GRU can also be considered a variation of the LSTM because both are similarly designed [31].
- Simple RNN: Simple RNN uses sequential data or time series data. So RNN works on the principle of saving the output of a particular layer and feeding this back to the input in order to predict the output of the layer [32].

For the evaluation of AI algorithms, it is essential to use metrics such as Precision, Recall, and F1-Score [33]. These standard metrics evaluate aspects of the algorithm. Precision 1, represents the number of data classified as belonging to a class, is the true positive, *Recall* 2, evaluates the system's ability to find all positive samples in the set, and F1-score 3, the weighted harmonic mean between precision and recall.

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

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

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

The true positives (TP) are the samples correctly classified by the classifier model and given by the positive class. The true negatives (TN) represent the same as the negative class. The false positive (FP) refers to the classifier result where the model is classified incorrectly for the positive class and the false negative (FN) incorrectly for the negative class. In addition, for a final assessment, another applied metric is the confusion matrix, which displays the distribution of correct and incorrect classifications for each class.

V. RESULTS AND DISCUSSIONS

In the previous section, we presented the experimental methodology for evaluating the proposed method for the HAR. We evaluated ways of collecting data from a wearable device to train and test the AI algorithms in this context. In this section, the results obtained from the tests with the data collected by the wearable device, the WPU, and the four SPU sensors are presented. In addition, we present our preliminary conclusions based on a graphical analysis of sensor data implementing the three AI algorithms.

Figure 3-a and Figure 3-b shows the data between two positions used for sensor calibration, which we can observe in approximately 60 seconds. We can notice greater oscillations in the second position (standing). This could be due to small movements of the user's legs or changes in foot positions. In the position (seated), we see no large variations. This means that the user remained most of the time without moving. In both readings, the K quaternion information remains practically constant.

Figure 4-a and Figure 4-b show the data collected by the sensors for two activities proposed in the case study of this work. The activities are walking on the street level and walking in an indoor environment with a slope. In both activities, we observed that there is a greater variation in relation to the calibration positions, which was already expected. In the activities of walking with inclination in the indoor environment, we can observe that none of the components of the quaternions

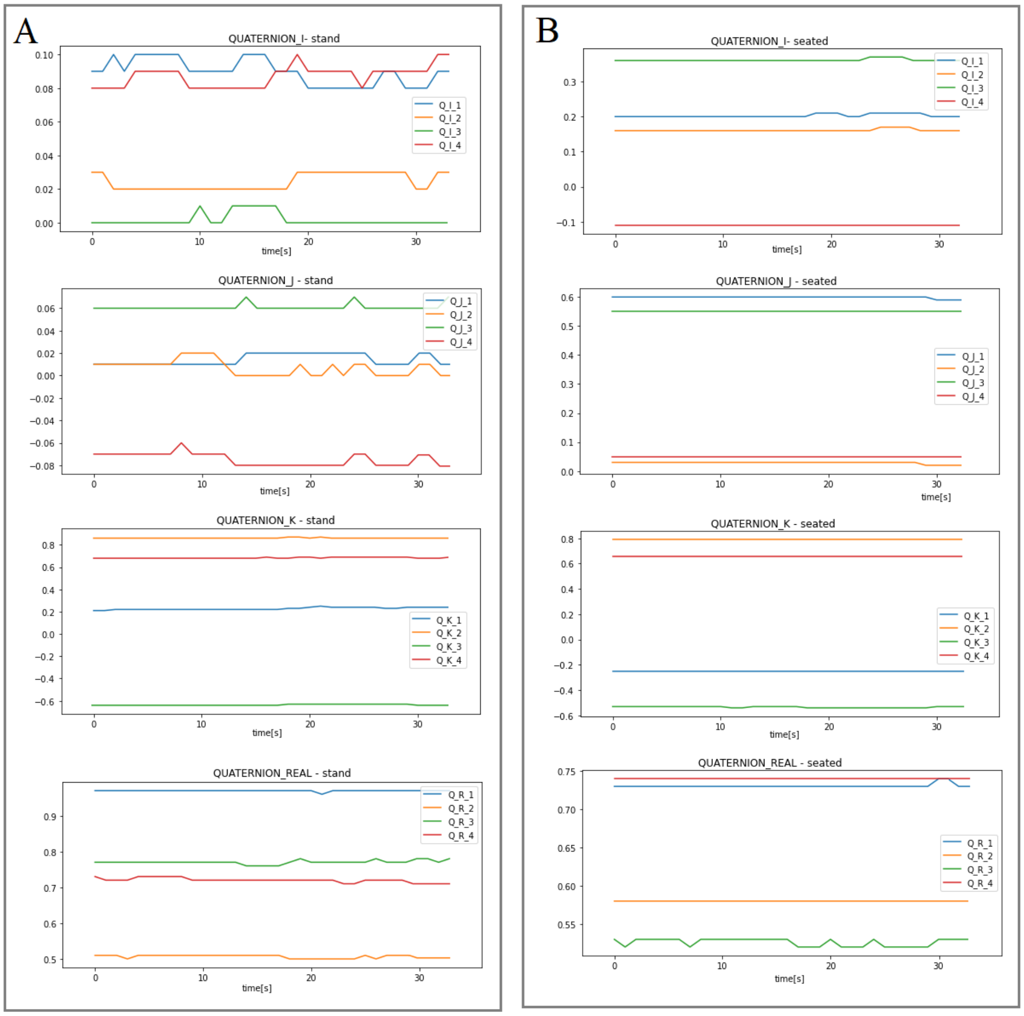

Fig. 3. A) Standing; B) Seated.

remains constant, and also the oscillations of the J components of the SPU1 and SPU3 sensors and the I components of the SPU2 and SPU4 sensors suffer greater oscillations. This is due to greater ranges of motion to perform this activity. Thus, with future analysis and modeling of AI algorithms, we can identify, for example, the physical effort of an athlete to perform a certain activity and thus provide a tool that helps him to gain performance.

A. HAR Algorithms - Training with Dataset

In this section, we show the results of training tests of the three AI algorithms used for this case study. Tables III, IV, and V present the results of validation metrics for the LSTM, GRU, and Simple RNN models, respectively. The studied algorithms reached a global accuracy superior to 98%.

Figure 5 shows the training results for three IA models. The graphs show a zero trend despite training oscillations in each epoch. Also, these results do not show overfitting, showing a satisfactory convergence for the model. Finally, after 15 epochs, the GRU model obtained a validation accuracy of 98%. Figure 6 displays the test results for Three AI models. In this test, we see that the model accurately classified the data between the four classes in the dataset.

We evaluated the IA models to standard metrics. For each class, we evaluated the precision, recall, and F1-score. We also evaluate the global average for each case. Table III displays the metrics for the LSTM, Table IV displays the metrics for the GRU, and Table V displays the metrics for the Simple RNN. The results indicate that the GRU had a slightly better performance when compared with both other options. The metrics of LSTM and Simple RNN indicate they have the same performance, but LSTM has a better Recall in the classification of iwuphill class.

TABLE III
METRICS FOR THE LSTM MODEL

	Precision	**Recall**	**F1-Score**	**Support**
seated	1.00	0.92	0.96	265
stand	0.99	1.00	0.99	726
walk	0.95	0.99	0.97	611
iwuphill	0.99	0.98	0.99	498
Macro average	0.98	0.97	0.98	2100
Weighted average	0.98	0.98	0.98	2100
Global Accuracy:	98%			

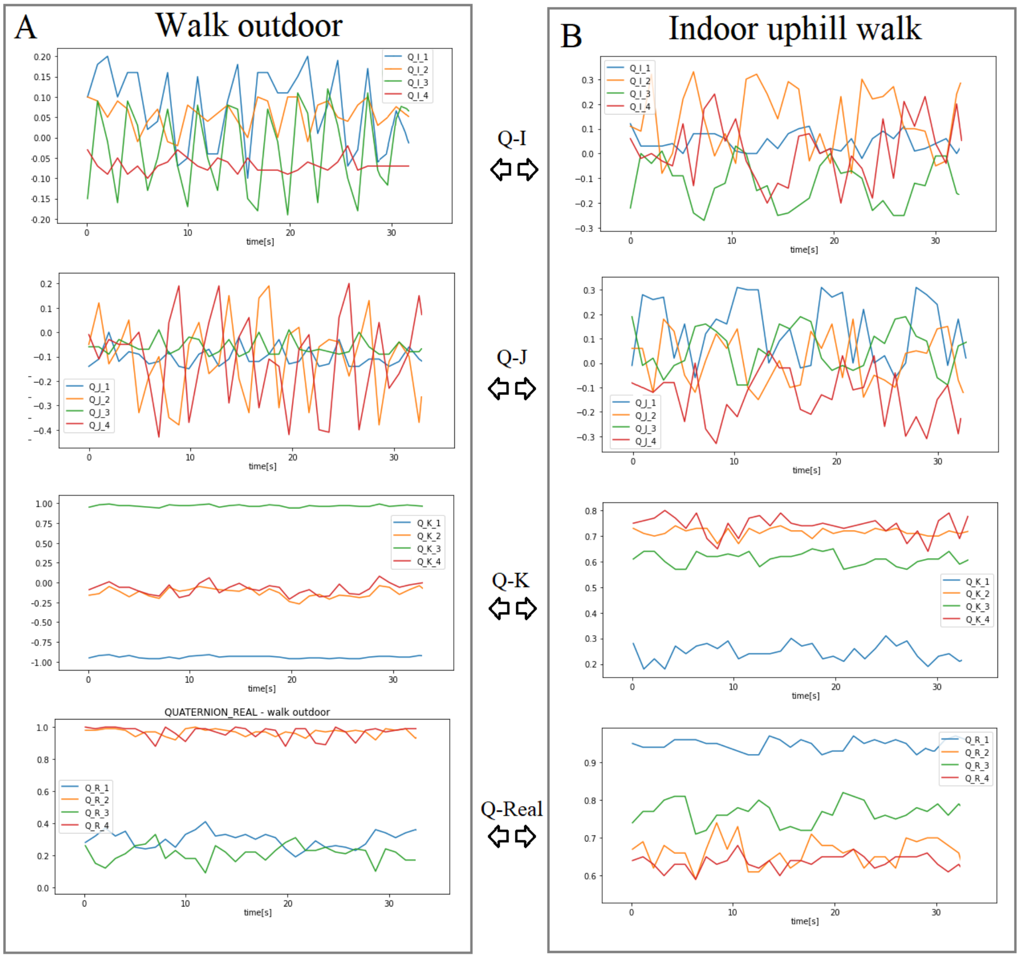

Fig. 4. A) Outdoor walk; B) Indoor uphill walk.

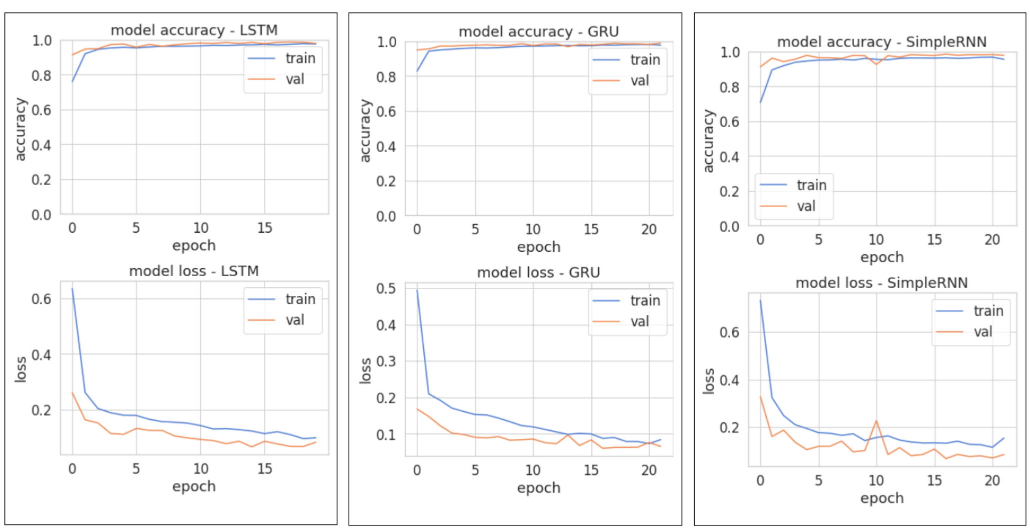

Fig. 5. Evaluation of the accuracy and loss values for the training and validation sets.

Semwall et al. [34] achieved 92% accuracy using a CNN algorithm to classify walking activity with data collected by the IMU. We show the efficiency of the sensors used with 9DoF and the fusion of received data for algorithm training, reaching an accuracy of 98%. Bijalwan et al. [35] achieved 98% accuracy using CNN-LSTM or har-based vision. With sensor-based HAR, we achieved 99% accuracy with a CNN-GRU. Also, we also achieved a superior accuracy of 96.37% achieved by Sravan et al. [36].

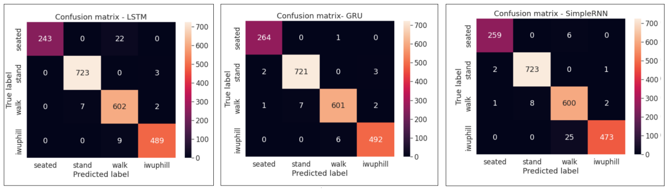

Fig. 6. Confusion Matrix.

TABLE IV
METRICS FOR THE GRU MODEL

	Precision	**Recall**	**F1-Score**	**Support**
seated	0.99	1.00	0.99	265
stand	0.99	0.99	0.99	726
walk	0.99	0.98	0.99	611
iwuphill	0.99	0.99	0.99	498
Macro average	0.99	0.99	0.99	2100
Weighted average	0.99	0.99	0.99	2100
Global Accuracy:	99%			

TABLE V
METRICS FOR THE SIMPLERNN MODEL

	Precision	**Recall**	**F1-Score**	**Support**
seated	0.99	0.98	0.98	265
stand	0.99	1.00	0.99	726
walk	0.95	0.98	0.97	611
iwuphill	0.99	0.93	0.96	498
Macro average	0.98	0.98	0.98	2100
Weighted average	0.98	0.98	0.98	2100
Global Accuracy:	98%			

B. Discussions

The prototype developed provides information about the walking activity performed by the user. In sports, such as running activities, the wearable device can help prevent wear and tear and injuries with an irregular stride or gait. It is possible due to the accuracy of the sensors that make up the device and the fusion of data through multiple sensors. On the other hand, individual sensors may have difficulty differentiating between some of these activities because they perform similar movements. Thus cross-checking was essential for AI algorithms.

One of the wearable device's main advantages is greater data capture accuracy. Using various sensors such as the IMU 9DoF, it was possible to obtain more profound information about the user's movement and achieve high accuracy with the CNN. Thus surpassing some existing works in the literature that do similar tasks.

VI. CONCLUSIONS

This work presents a case study for recognizing human activity using an AI wearable device. The first sections of the paper showed that the HAR has applications in different areas, for example, in sports. The HAR task describes the set of techniques used to recognize the behavior of humans by computer devices. There are several approaches to this task, with single or multi-sensors. In our multi-sensor wearable device, we achieved good results in training the algorithm for HAR.

Often, authors also separate the HAR problem into visual-based or sensor-based. In both cases, AI has an important role, being present in most of the current solution proposals. This topic has an essential approach for applications with wearable sensors, as presented in this work. This is due to the advances of these more compact devices with the possibility of implementing AI algorithms in their structures. In several sports approaches, authors propose the usage of sensor-based HAR using wearable units. Finally, most approaches employ CNNs or RNNs to perform HAR tasks.

We propose a system that employs wearable sensors to evaluate performance in walking and trekking activities. We studied the possibilities of using recurrent neural networks in performing these tasks. The integration of four sensors called SPUs was essential for the application of this case study. By merging the data, the three AI algorithms show an overall accuracy of over 98%. This shows that the device can be applied to other case studies, for example, to help runners by delivering precious information to improve athletic performance.

The prototype has limitations, such as dimensions and quantity for testing with more users. In future work, it is expected to reduce its form and perform analyses with more users. Also, we will collect new information on running activities to measure athletic performance by users by IA models.

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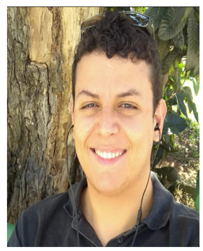

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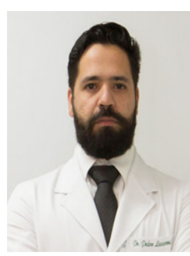

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