Towards novel smart wearable sensors to classify subject-specific human walking activities

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***Abstract*—In this century, intelligent devices are increasingly present in our lives, such as at work, in sports, or in household chores. In this context, wearable devices can help people with health monitoring or sports activities. With the integration of artificial intelligence (AI), these devices can identify injuries in athletes or care for the elderly in rehabilitation from human activity recognition (HAR). AI techniques, such as image classification or HAR, are commonly applied for pattern recognition. In this context, we seek to develop a smart wearable device to recognize walking activities. To improve the identification of these tasks through AI algorithms, we propose the fusion of data between four sensors called SPUs. Each SPU has NodeMCU ESP-32 and BNO080 IMU hardware in its architecture. The data from these hardware provides information in high precision. A Raspberry pi zero W collected this information. After extracting and manipulating this data, we trained a deep learning model. The model accuracy was higher than 92% reaching an overall accuracy of 97%. Therefore, the smart wearable device showed a new tool for recognizing walking activity, which could be applied in the future to recognize more complex tasks.**

***Index Terms*—HAR, LSTM, Wearable, Sensors, Walk, AI.**

I. Introduction

Computing devices are being improved due to advances in internet of things (IoT) technologies and AI, enabling new applications. Given this, wearable sensors are increasingly present in our lives [1]. Using these devices in HAR, such as walking monitoring, can provide valuable information about the user's lifestyle or health status [2]. The integration of wearable sensors in the HAR can help people in health care, such as detecting neurological disorders that affect motor activities, home rehabilitation, and evaluating the effectiveness of treatments [3].

Systems intended for HAR usually use deep learning methods to identify tasks based on data sent by sensors [4]. This is due to the efficiency of these models in the learning phase, as they do not entirely depend on pre-processed data like machine learning models, so their performance is higher in performing these tasks. Wearable devices commonly used in this context are smartwatches, as they have several integrated sensors, such as an accelerometer and gyroscope [4], and smartphones which, in addition to having several sensors in their physical system, interface with real-time applications [5]. The data collected and stored by these devices provide the information for intelligent algorithms and consequently present significant decisions to the user.

Single sensors have disadvantages in using the generated data compared to other wearable devices for HAR [6]. Sames studies have proposed data fusion methods where they combine information from multiple sensors to increase the reliability of the systems for the HAR, which addresses possible problems in recognition of activities by generated data [7]. However, for the system to perform an activity recognition efficiently, it is necessary to integrate other sensors into the recognition system [8]. Thus, the work presents the HAR from the data received by multiple sensors. This becomes possible due to the use of deep learning methods as they perform data learning with data fusion techniques [9].

Therefore, we propose a novel smart wearable device to HAR. The main contribution of this work is: The main contribution of this work is:

- The proposal of novel smart wearable sensors to classify walking and stand positive for future sports analysis.

For that matter, Section II presents the theoretical references used in this work. In Section III, we describe the system's main features. We present the methodology for validating aspects of this system in Section IV. In Section V, we display the results of an analysis of the data and its interpretation. Finally, in Section VI, we discuss the results obtained and a comprehensive discussion of this work and future applications.

II. Theoretical references and related work

This section presents the results of some literature reviews with an overview of wearable devices. It covers the fundamental aspects and applications in this context.

A. Wearable Systems

Wearable systems can be defined as a device that involves a type of technology that the user can wear or as an accessory on the body, for example, watches or headphones [10]. This type of device is expanding in the market and research areas [11], a promising area that will likely be present in several niches in the coming years.

The main components of wearable devices are micro-controllers, sensors, actuators, and Software [12]. The communication between wearable systems or sensors can be done through textile conductors, which are flexible and used for the construction of circuits. Also, for wireless connectivity, wi-fi or BLE has lower power consumption than classic Bluetooth [13]. Another important factor is the electrical energy used to run the entire system. This energy can be needed through portable batteries, being independent for each component of the system or centralized for the entire wearable system.

Thus, wearable devices can be simple, including sensors and raw data capture [14]. However, improved solutions, with integrated AI algorithms and real-time image processing techniques [15], expand the possibilities of using this technology for the end-user.

B. Wearable Systems Design

Understanding wearable systems and their components is essential to define the design and architecture to optimize the resources used [16], such as memory and energy consumption [17]. The way the components are organized can define their architecture. In a decentralized architecture, tasks are divided, and there can be communication between hardware and sensors via wireless or Bluetooth [18]. In a centralized architecture, the task is processed on the leading hardware, and the components are connected directly to the hardware [19].

In developing the wearable device in this work, we tried to distribute the task of sending information in four sensors. This information is sent via Bluetooth to a central device to store the data. Thus, we preserve the device's energy resources that are resource constrained.

C. Applications of Wearable Systems to HAR

In the literature, we find applications of HAR with wearable sensors [20] [21]. These applications can be integrated into different areas, such as the health area [22]. One of the applications in this context is the identification of a neurological disorder in the user, such as Parkinson's [23].

However, these works found in the literature use simple sensors for activity recognition, as well as a single sensor [24]. These aspects differ from the proposed work because, in addition to using four sensors in accord with Figure 1, the hardware used has high precision in providing space information.

D. Wearable Edge AI

The AI integration in wearable systems is intended to provide users with information about data collected and processed at the device's edge. There are still many challenges in applying Deep Learning (DL) in a wearable device [25], which can be due to a large number of neurons and layers of the network. Also, privacy and system latency problems are to be solved in this context.

Deng et al. [26] propose a model adaptation, Framework Design, and Processor Acceleration to solve a resource restriction. They show that these challenges can be addressed through new system architecture, thus increasing AI performance. Other literature shows that there is difficulty in running an AI model on a wearable device due to the requirements of the system [27]. The authors apply low latency offload techniques to solve the classification problem and improve accuracy for detecting critical points on objects.

III. System Description

In the previous sections, we presented the context and importance of the presented work and the main concepts and related work within this topic. In this section, we present the proposed system architecture, covering the hardware used by the sensors and its elements.

A. Wearable Sensors

The data used throughout this project is gathered and pre-processed using a specific wearable solution attached to the user's lower body. This device trusts a set of high-end IMUs (Inertial Measurement Unit) to collect the leg's physical movement.

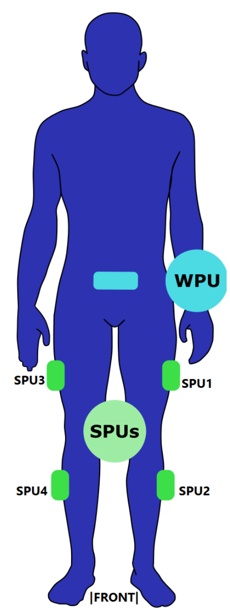

Fig. 1. Wearable device used to collect individual's movement data. Highlighted areas indicate the location where each device is positioned.

Within this project scope, two distinct classes of hardware have been used and compose the final solution: The Sensor Processing Unit (SPU) and the Wearable Processing Unit (WPU). Figure 1 outlines the position of each element when attached to the individual's body. Briefly, the data is collected in a distributed manner using the SPUs, then forwarded to the WPU. At the WPU, received information may be pre-processed and sent to an external server or stored locally within an SD-card (flash memory).

1) Sensor Processing Unit – SPU: The SPU uses four different units attached to the user's legs to collect raw real-time information according to the activities performed by the individual. Each of these units embeds the following hardware:

- BNO080 IMU: 9-degrees inertial sensor comprising accelerometer, gyroscope, and magnetometer readings. It is used to retrieve body parts' physical orientation.
- Lithium-Ion battery;
- NodeMCU ESP-32: Hardware platform based on Espressif ESP-32 solution. It is in charge to read data sensed by IMU and continuously forwarding it to WPU hardware using the Bluetooth interface.

2) Wearable Processing Unit – WPU: The WPU comprises hardware in charge of receiving data collected by the SPUs, sequencing it – timestamping each received packet – and: a) Store it locally for further analysis, or b) Send it to a remote server/service using the IEEE 802.11 wireless interface. The WPU embeds the following hardware:

- Raspberry Pi Zero W:
- Humidity and temperature sensors:
- BNO080 IMU: 9-degrees inertial sensor comprising accelerometer, gyroscope, and magnetometer readings. It retrieves upper body physical orientation, temperature, and humidity.

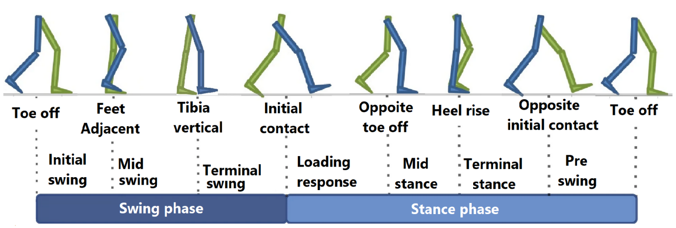

Fig. 2. Full walk cycle [28]

B. Long short-term memory (LSTM)

Long short-term memory (LSTM) are recurrent neural networks (RNN) capable of classifying sequential data due to their learning memory storage characteristics [29] [30]. These deep learning networks are commonly used for event recognition by time series analysis, as in HAR [20].

Data from the SPUs is sent to the raspberry pi zero W over time. With this, the fusion of data from the four sensors forms a specific event over time. This condition enables the LSTM to classify the activity within a specific time series interval.

IV. Experimental Methodology

In the last section, we presented an overview of the proposed system. This proposal embraces the usage of an AI algorithm for HAR. This section presents the experimental methodology to validate some aspects of the proposed solution.

A. Data Preparation

We mount a database [31] to validate the use of the smart wearable device. This dataset has three categories: Walking, standing, and sitting. The four SPUs send data to the Raspberry pi zero W at a particular sampling frequency, with a specific range of values. The signal received by the Raspberry pi zero W is composed of the components I, J, K, REAL, and Radians, corresponding to the quaternions. Although the sensors are identical, the constructive aspects can influence data sending at a non-constant sampling frequency.

The input data for training the algorithm must have a normalized format, for example, a certain number of samples per second over time. The literature suggests that about 50Hz is an adequate sampling rate that allows for modeling human activities [32], so it does not interfere negatively with the machine learning model results. It is also important to emphasize that, for the purpose of this study, the data were collected by a single person, thus ensuring the homogeneity of the information. The pre-processing of the collected data sets was carried out to make them homogeneous in terms of the sampling rate to maintain the data's homogeneity.

B. LSTM model

For developing the deep learning model with LSTM, we adopted a value of 10 for the sliding window length with steps equal to 2. We see that the model achieves better precision in this small interval compared to steps and sliding window lengths with superior values. The sequential LSTM model is composed of the first bidirectional layer with orthogonal kernel and L2 regularizers, as well as a Flatten layer, another Dense layer of 128 Relu activation followed by a dropout of 0.2, and finally, another Dense layer with softmax activation. Also, the model was compiled with the Adam optimizer using the categorical loss function cross-entropy and standard metric accuracy. However, the model was trained for 20 epochs, an adequate amount for this amount of input data in the algorithm.

The choice of metrics is essential for evaluating the AI algorithm [33]. For evaluation of the model, using the following standard metrics: Precision, representing the number of data classified as belonging to a class, is the true positive; *Recall*, which evaluates the system's ability to find all positive samples in the set; F1-score, the weighted harmonic mean between precision and recall.

C. SPU's

For this matter, we make a data collecting in a fixed position to make calibration of the algorithm according to Figure 1. Before building the AI model, data analysis was performed to understand how the sensors send data to the Raspberry pi zero W. The sensors were positioned as shown in Figure 1. We considered the four components, I, J, K, and R, to compose the training data. These components receive the following names respectively:

- Quaternion I + ID = Q-I-ID
- Quaternion J + ID = Q-J-ID
- Quaternion K + ID = Q-K-ID

- Quaternion R + ID = Q-R-ID

V. Results

In the last section, we presented the experimental set for evaluating the proposed method. We evaluate significant features for the creation of sensors. In this section, we present the results obtained from the proposed tests. Also, we display our preliminary conclusions based on each result.

A. Sensors Performance Test

Fig. 3. Cycle for walking activity: collecting data.

The sensors collected the data for the walking activity as shown in Figure 3 and also in two other positions, sitting and standing. For the analyses, 30 executions of the systems were performed for each of the three states. After each run, we turned off the equipment and recharged the sensors and the Raspberry pi zero W battery. This measure was necessary to ensure that the system always worked the same way.

Figure 4 shows data collected by the sensors for the walking activity as shown. In the time interval of approximately 60 seconds, we can see that in this activity, the components of the lower sensors suffer oscillations with larger amplitudes compared to the upper sensors. In the Quaternion-Real component, this information is more evident. Thus, we see the importance of adding four sensors to perform HAR in this context.

Figure 5 shows the data in a time window of approximately 60 seconds, representing a person in the standing position. We can see more considerable oscillations between the intervals of 40 to 60 seconds. This observation can be due to small movements of the user's foot position, being rotations of the foot positions outwards or inwards. It is also noted that most of the time, the data remains with almost constant values.

Finally, in Figure 6, we have the last position under analysis, with the user seated. In this window of data components, we observe that there are not four significant amplitude variations in the sensors. This result is why in this temporal window, the static is used, with almost imperceptible movements. Slight movements can be important to analyze in future work. As in the literature review, recognizing neurological diseases, such

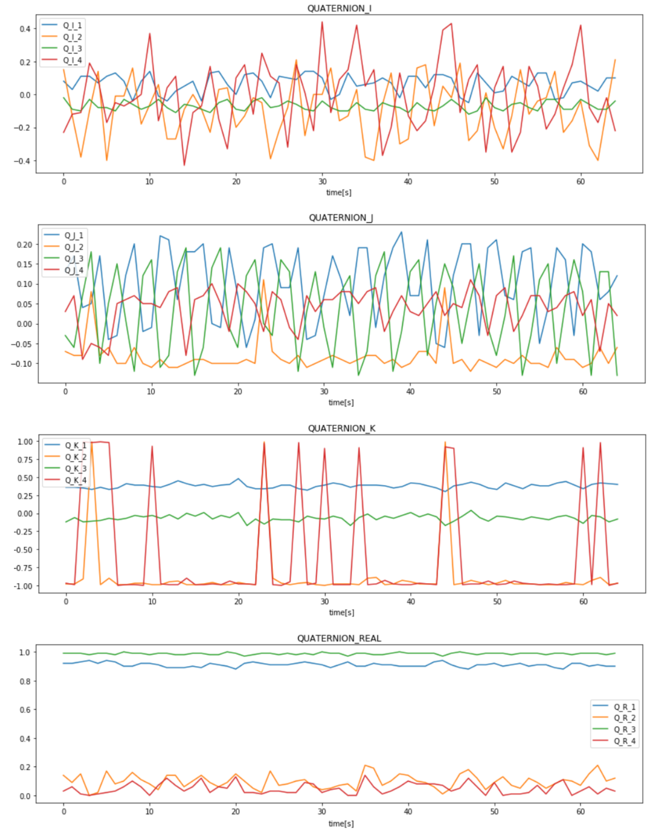

Fig. 4. Walk

as Parkinson's, can be with the help of intelligent systems based on the data observed by these wearable sensors.

B. LSTM - Performance Tests

This section shows the results of training tests on the deep learning model developed for HAR. Table I, presents the results of the validation metrics of the AI model mentioned in section IV. For the precision, recall, and F1-score of the model, the results were higher than 92%. Thus, the LSTM model used presents a high performance in this context.

TABLE I
METRICS FOR THE LSTM MODEL

	Precision	**Recall**	**F1-Score**	**Support**
Seated	1.00	1.00	1.00	68
Stand	0.98	0.95	0.95	63
Walk	0.92	0.98	0.95	59
Macro average	0.97	0.97	0.97	190
Weighted average	1.00	1.00	1.00	190
Global Accuracy:	97%			

Figure 7 shows the training results for the LSTM model. Despite containing some oscillations in error at each epoch in training, it is noted that there is a tendency towards zero. Thus, these results do not show overfitting, showing a satisfactory convergence for the model. However, after 26 epochs, the model obtained a validation accuracy of 97%. Finally, Figure

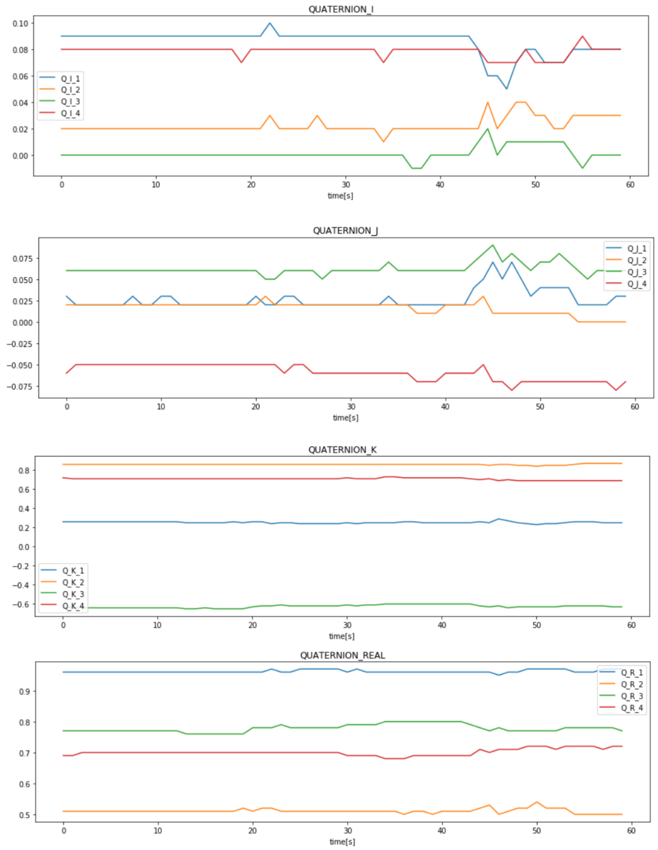

Fig. 5. Stand

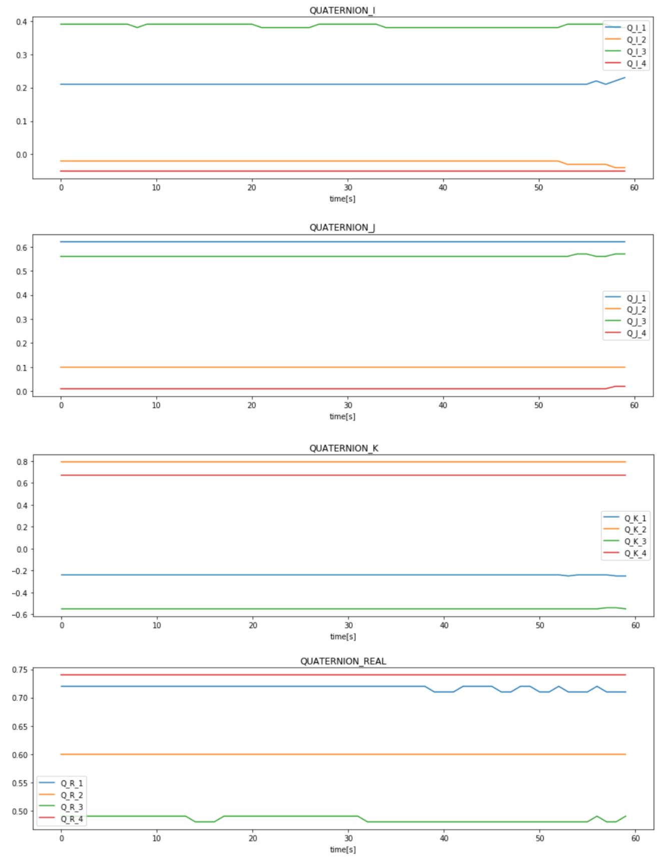

Fig. 6. Seated

8 displays the results for the test for LSTM model. In this test, we see that the model accurately classified the data between the three classes.

The intelligent wearable device developed in this work showed satisfactory results for recognizing walking activity. Using single sensors for HAR can present similar information in different activities. Thus, using the four sensors was an essential aspect of constructing the deep learning model. for future work, we can use this smart wearable device in other HAR with high performance.

VI. Discussion

This work presents the importance of smart wearable devices in the HAR context for walking activities. In the first sections of the work, we understand the need to develop a new smart wearable device and the constructive aspects necessary for integrating a deep learning model.

The literature review showed that HAR using wearable devices allows applications in several areas. The HAR theme has become a relevant approach in mobile computing. This is due to the increasing development of new technologies such as more compact hardware and the increase in the computing powers of these devices, which allows the integration of increasingly efficient AI algorithms. Thus, it creates new application perspectives for new wearable devices in the context of HAR.

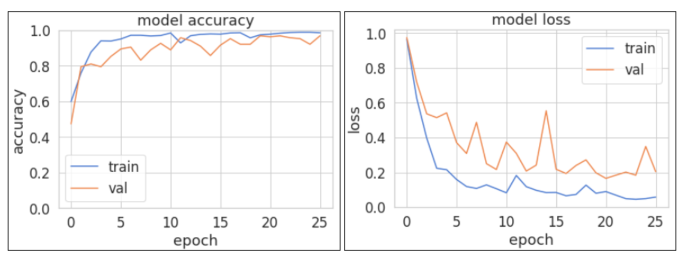

Fig. 7. Evaluation of the accuracy and loss values for the training and validation sets.

Extracting information is challenging in the HAR pipeline based on wearable sensors. The complexity of the data, such as the sampling rate at which the data is sent, can influence the performance of the AI model. Thus, we adopt wireless communication methodologies to avoid problems in data transmission to the WPU. In the data collection, we tried to leave the sensors always positioned uniformly, allowing our samples to present more homogeneous results without many variations.

Data fusion between the sensors proved to be effective for the recognition of walking activity. With these input data in the LSTM model, we achieved a high accuracy of 97%. Thus, with the aid of the AI model, the new wearable device proved to be effective for the recognition of walking activity based

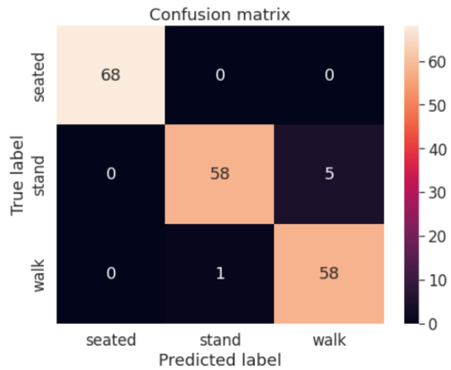

Fig. 8. Confusion Matrix

on the extraction of information by four SPU sensors sent to the WPU.

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