Article **Journal of Technical Invention**
June 2023 Vol.7 No.19 1-8

# Implementation of a BSN for the detection of activities during the coffee harvest

# Implementación de una BSN para la detección de actividades durante la recolección de café

MAGÍN-MURILLO, Dagoberto[1]†*, SÁNCHEZ-MEDEL, Luis Humberto[2], SOLÍS-JIMÉNEZ, Miguel Ángel[1], MELCHOR-HERNÁNDEZ, César Leonardo[1] and TEJEDA-GARCÍA, Rafael[1]

[1]*Instituto Tecnológico Superior de Huatusco*
[2]*Instituto Tecnológico de Orizaba*

ID 1st Author: *Dagoberto, Magín-Murillo* / **ORC ID**: 0000-0001-7138-9074, **CVU CONAHCYT I**D: 1194039

ID 1st Co-author: *Luis Humberto, Sánchez-Medel* / **ORC ID**: 0000-0002-6783-585X, **CVU CONAHCYT ID**: 655387

ID 2nd Co-author: *Miguel Ángel, Solís-Jiménez* / **ORC ID**: 0000-0002-8125-0989

ID 3rd Co-author: *César Leonardo, Melchor-Hernández* / **ORC ID**: 0000-0003-2154-6654

ID 4th Co-author: *Rafael, Tejeda-García* / **ORC ID**: 0009-0003-7994-8055

**DOI:** 10.35429/JOTI.2023.19.7.1.8 Received January 12, 2023; Accepted June 24, 2023

**Abstract**

Currently, Body Sensor Network (BSN) body sensor networks are generating great interest due to applications in different scientific and industrial environments, they form a technology that allows data acquisition for research and process control. That is why the design of an architecture is proposed, based on networks of body sensors for real-time analysis during the coffee harvesting process because the workers are subject to repetitive physical movements and thus generate a knowledge base and a machine learning model to present the mathematical models with the intention of justifying the decisions made from the coffee harvesting activity. The suit consists of two modules placed on the arms of the people and another on the thorax, which are the reference points for taking the data, thus making use of today's wearable devices.

**Acquisition, Movements, Models**

**Resumen**

En la actualidad las redes de sensores corporales Body Sensor Network (BSN) están generando gran interés debido a las aplicaciones en diferentes ámbitos tanto científicos como industriales, forman una tecnología que permite la adquisición de datos para la realización de investigaciones y control de procesos. Es por ello que se plantea el diseño de una arquitectura, basada en redes de sensores corporales para el análisis en tiempo real durante el proceso de recolección de café debido a que los trabajadores están sujetos a movimientos físicos repetitivos y así generar una base de conocimientos y un modelo de Machine Learning para presentar los modelos matemáticos con la intención de justificar las decisiones tomadas de la actividad de recolección de café. El traje consiste en dos módulos colocados en los brazos de las personas y otro sobre el tórax, los cuales son los puntos de referencia para tomar los datos, por lo que se logra hacer uso de los dispositivos vestibles de la actualidad.

**Adquisición, Movimientos, Modelos**

**Citation:** MAGÍN-MURILLO, Dagoberto, SÁNCHEZ-MEDEL, Luis Humberto, SOLÍS-JIMÉNEZ, Miguel Ángel, MELCHOR-HERNÁNDEZ, César Leonardo and TEJEDA-GARCÍA, Rafael. Implementation of a BSN for the detection of activities during the coffee harvest. Journal of Technical Invention. 2023. 7-19: 1-8

*Correspondence to Author (e-mail: magindago@gmail.com)
† Researcher contributing as first author.

 

## Introduction

Growing coffee is a job that involves a lot of physical activity and forced postures, which increases the risk of muscle injuries. It is important to improve the coffee harvest conditions to make it more comfortable and ergonomic, as well as reduce the weight load and work time. These improvements are necessary to prevent musculoskeletal disorders and improve the health of agricultural workers, considering the economic importance of coffee cultivation. One solution is to use a network of body sensors to record and analyze the movements and signals of the human body, allowing a better understanding of ergonomic risks and the identification of more effective solutions. The demand for these devices continues to grow, which has led to improvements in their quality of service and reliability by applying them in different examples: weather forecasting, identifying medical disorders, predicting customer purchasing preferences, detecting and classifying signals, controlling robots in manufacturing and vehicles, and support of bionic implants (Golden, 2020).

A BSN is an independent system used to monitor a person's activities of daily living, (Sangwan & Bhattacharya, 2015), The functionalities and ease of use of these systems have also received an important boost thanks to the diffusion of portable devices such as wearable devices that represent the complement for portable nodes, becoming an increasingly important part of technology and their use is going from be simple accessories to more specialized and practical applications(Lai *et al*., 2013).

The article is organized in different sections. The first section focuses on the state of the art, reviewing what has already been investigated in relation to the use of inertial body sensors. In the methodology section, it is described how the research was carried out, what techniques and tools were used to obtain the results. The functional tests section focuses on showing the results obtained by implementing the proposed techniques with decision tree algorithms that have the advantage of being easily expressed as rules. (Dreiseitl & Ohno-Machado, 2002).

In the future proposal section, possible improvements or future applications of the research are proposed. Finally, in the conclusions section, the most important findings are presented and the results obtained are summarized.

## 1. State of the art

As mentioned, smart wearable devices have allowed the development of wearable technology at an accelerated rate adapted for various applications during the last years (John Dian et al., 2020). Wearable devices have become an easy tool for the recognition of human activities and it is common to find devices with temperature sensors, gyroscope, accelerometer, among others, the main added value is used to capture body movement data, can provide various monitoring and scanning functions, including feedback or other sensory physiological functions (Lee & Lee, 2020).

Advances in the development of machine learning algorithms have allowed these advances and generated, of course, a very broad domain (Shalev-Shwartz & Ben-David, 2013). The wearable devices that we know and use today have gained popularity thanks to the market introduction and marketing of these products as shown in Figure 1.


**Figure 1** Wearable Device

### 1.1 Accelerometers

Accelerometers are sensors found in wearable devices because their sensing capabilities range from different types of linear and gravitational accelerations. The measurement capabilities allow the data that has been obtained to be programmed for different uses, for example, when a user runs, it can generate the maximum speed and acceleration (Aroganam *et al*., 2019).

ISSN 2523-6792

### 1.2 Gyroscopes

Gyroscopes are another common type of sensor found in wearable devices. The main difference with the accelerometer is that it exclusively measures angular accelerations, the advantage of combining both is to filter errors and increase the precision of the monitored data. *(Aroganam et al.*, 2019).

In areas such as health, the use of BSNs can be implemented, then the design of a wireless network of body sensors for the integrated acquisition of signals that is made up of wireless modules for the acquisition of biosignals is described, the objective of the work was design and develop a wireless Body Sensor Network system that allows the synchronous acquisition of cortical and muscular activity for the evaluation of sensory responses, due to the architecture of the system and the good quality of the results obtained, the proposed device represents an advance in state-of-the-art technology in terms of the simultaneous acquisition of electroencephalography (EEG) signals and high-density surface EMG (HD-sEMG).

This is how (McClure *et al*., 2020) shows an investigation where a breathing analysis system was developed using data from the accelerometer and gyroscope implemented in wearable devices placed on the chest and abdomen to detect different breathing patterns to solve in emergency medical situations.

To do this, various respiratory events were simulated and synthetic data sets were constructed by injecting annotated examples of the various patterns into segments of normal respiration. In order to obtain the results, the convolutional neural network artificial intelligence model was used to detect the location of each event and classify it into one of the previous types of events.

A mean score of 92% was achieved for normal breathing, 87% for central sleep apnea, 72% for cough, 51% for obstructive sleep apnea, 57% for sighing, and 63% for yawning.

The results of this study demonstrate that the use of wearable devices to analyze movement data from the thorax and abdomen combined with artificial intelligence models provides an unobtrusive means of monitoring breathing pattern and could have applications in medical situations.

Critical as the detection of sleep apnea at home and the control of respiratory events in patients with mechanical ventilation in the intensive care unit. In (Sattar *et al*., 2019) it is described how BSN systems that use inertial sensors are replacing video-based systems to monitor performance in athletes, and this considerably reduces the work involved in installing the video camera, as well as the calibration procedure.

The important feature of the BSN system is the integrated way of creating a small portable device with computational power to process the data using various analysis techniques to monitor and improve performance in sports. The work carried out by (Chen, 2021) also considers the use of wearable devices to evaluate the performance of athletes during sports activities. The process involves recording movement variables at a high enough sampling rate throughout a series of tests to monitor training load, capture, and interpret data.

To carry out the analysis, he proposes the use of the Support Vector Machine (SVM) supervised learning algorithm to guide training and monitor athlete muscle measurement to result in improvements in measures related to poor physical health effects.

## 2. Methodology to develop

To develop the artificial intelligence model, the following steps described in Figure 2 should be considered.

ISSN 2523-6792

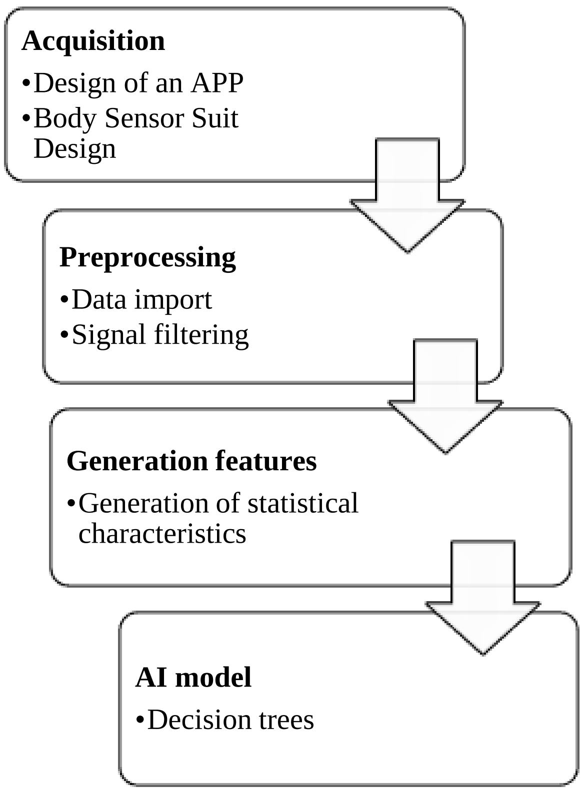


**Figure 2** Methodology to develop

## 2.1 Data acquisition

In the acquisition stage, the objective is to obtain the input data to be able to train the intelligence model and thus be able to classify the activities shown in Figure 3. Because the activities are labeled, supervised learning is applied.

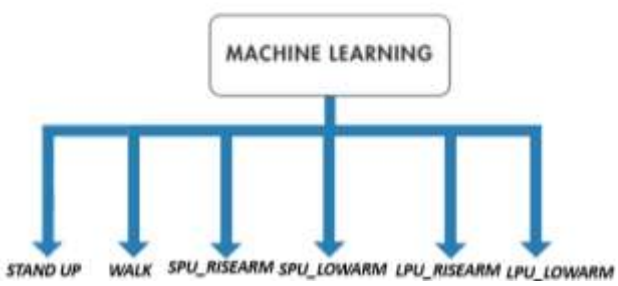


**Figure 3** Activities to classify

To carry out the acquisition it is necessary to have the wearable device, which users must carry to carry out the activities throughout the day, for this reason the 3 modules shown in Figure 4 were modeled in 3D to later print the parts and start with data acquisition tests.

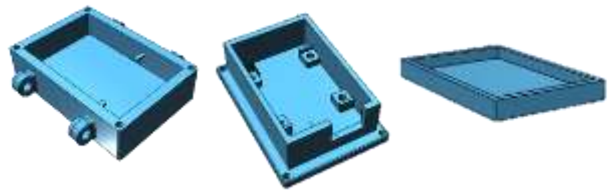

**Figure 4** Wearable Device 3D Model

Inside the wearable device, the electronic components are assembled to acquire the data, which consists of a 3.7-volt LiPo battery as seen in Figure 5, due to its rechargeable characteristics, as well as the OpenLog Artemis, shown in Figure 6, sensor that includes an IMU for integrated recording of accelerometer data and triple axis gyroscope.

**Figure 5** 3.7V Lipo Battery

**Figura 6** OpenLog Artemis

For the acquisition of data, the BSN is used on the reference points of the users, which are the right arms, left arms and on the thorax, as shown in Figure 7.

ISSN 2523-6792


**Figure 7** User-implemented modules

During the tests, the activities are labeled with the help of an application developed in Android to classify each action carried out by the user as shown in Figure 8. The activities are repeated until the data for each activity to be classified is available. The obtained data is stored in a text file as it is easy to work with a flat file format, such as text or CSV, and it makes it easy to import data for processing.


**Figure 8** Data acquisition

## 2. Preprocessing

Machine learning algorithms are not smart enough to differentiate between noise and valuable information, that is why before using the data for training, Figure 9 shows the signals obtained directly from the sensors, it is for Therefore, we must ensure that they are clean and complete, for this the preprocessing must be carried out.

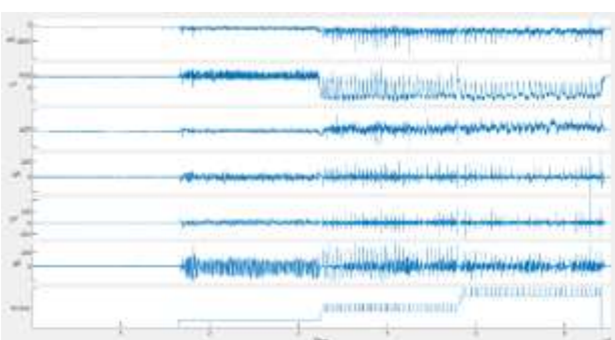

**Figure 9** Signals without preprocessing

To carry out the preprocessing, it is carried out using the temporary window method where only small parts of the signal are analyzed through a temporary window where the width is defined depending on the frequency with which the data was obtained and thus it slides along. of the whole signal.

Figure 10 shows the processed signal eliminating outliers.

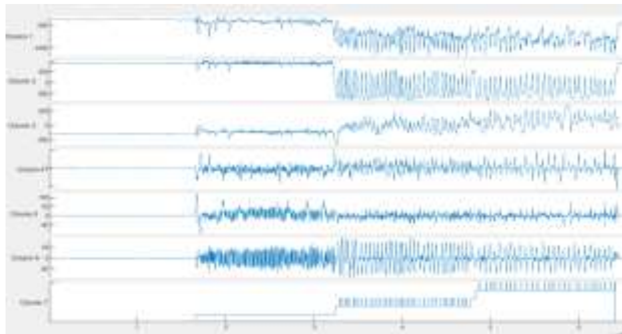

**Figure 10** Preprocessed signal

## 3. Generation of features

For the phase of extraction of characteristics from the knowledge base, it consists of making use of these characteristics as input data for a classifier that allows to improve the results obtained in the classification, in comparison if these are used directly from the data obtained by the device. wearable. The characteristics obtained are representative according to the temporal and frequency domain that is taken into account and allow the creation of different groups to verify which of them achieves a better result when classified. The most commonly used features are shown in Table 1

| Selected features | |
|---|---|
| Mean | Returns the mean of the elements of the first dimension of array. |
| Harmmean | Calculates the harmonic mean of a sample. |
| Kurtosis | Returns the kurtosis sample. |
| Median | Returns the mean value. |
| Mode | Returns the value that appears most frequently. |
| Min | Returns the least elements of an array. |
| Max | Returns the maximum elements of an array |
| Peak2peak | Returns the difference between the maximum and minimum values. |
| Rms | Returns the root mean square (RMS) value of the input data. |
| Skewness | Returns the skewness of the sample. |
| Std | Returns the standard deviation of the elements. |
| Sum | Returns the sum of the elements in the first dimension of the array. |
| Trimmean | Returns the mean of the values. |
| Var | Returns the variance of the elements. |

**Table 1** Statistical characteristics

ISSN 2523-6792

To carry out the generation of statistical characteristics, the code was made using the MATLAB® programming language.

## 4. Artificial Intelligence model

To carry out the machine Learner model, it is done with the Classification Learner application of the MATLAB® software, Figure 11, which is in charge of training models to classify data. With this application, you can explore supervised machine learning using various classifiers, explore the data, select its features, specify validation schemes, train models, and evaluate the results. To carry out the automated training, it is carried out with the decision tree classification model of Figure 12, due to the fact that automatic learning is supervised and that it provides a set of labeled data.


**Figure 11** Classification Learner

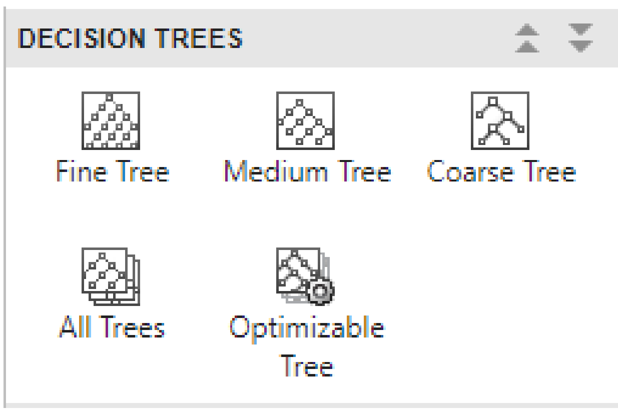


**Figure 12** Decision Trees

When building your model, you should start with something simple; since it will be faster to execute and easier to interpret, so the coarse Tree is generated, which shows a prediction of 80% of the classification of activities, as shown in Figure 13. To see how it works, generate the confusion matrix of Figure 14, to compare the classifications made by the model with the actual class labels.

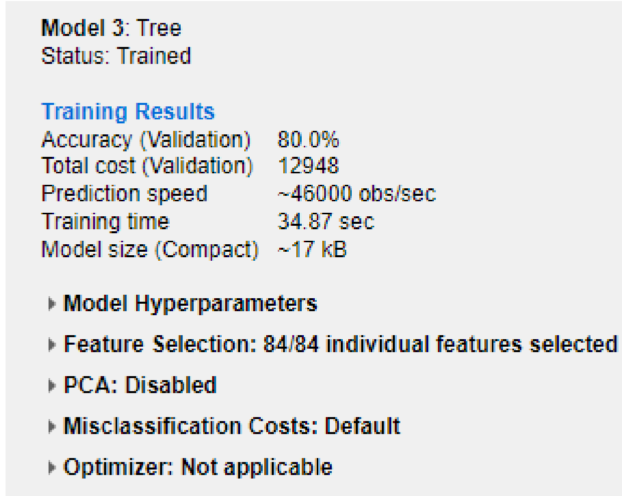


**Figure 13** Summary


**Figure 14** Confusion matrix

One or more classifiers can be automatically trained to compare the validation results and choose which is the best model that works for the classification of activities. For the Coarse Tree of Figure 15, it shows that our model has problems distinguishing all the activities, so the model must be trained again with a medium level, to improve the prediction or train the Fine Tree.

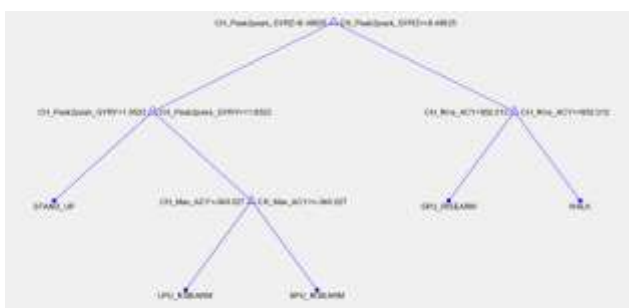

**Figure 15** Coarse Tree

ISSN 2523-6792

## Results

To obtain a better precision of the model obtained, the Fine Tree algorithm is trained, which returns an accuracy of 97.1% Figure 16, compared to 80.1% for the coarse tree. The confusion matrix of Figure 17 also shows an improvement in the results, it shows a diagonal with cells in blue, which indicates the true values, and the results obtained in the TPR column.

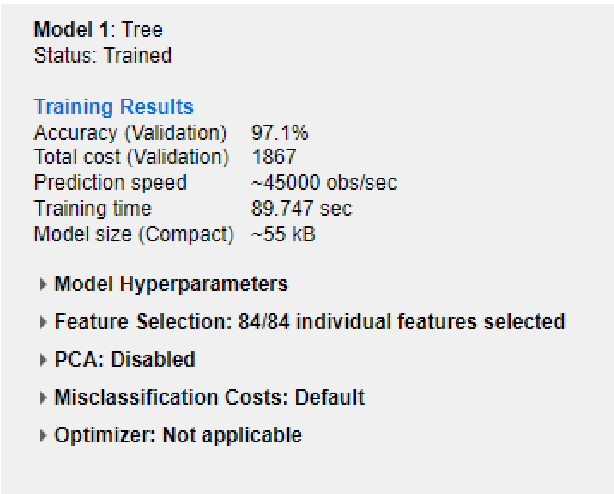


**Figure 16** Summary Fine Tree

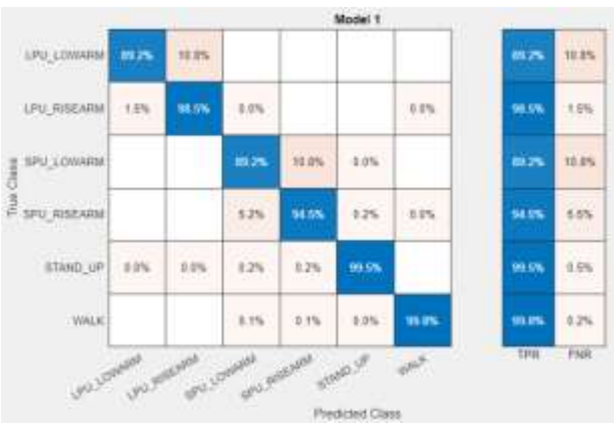


**Figure 17** Confusion matrix Fine Tree

Figure 18 shows through the ROC Curve the different comparisons that the algorithm makes to carry out the classification of the activities carried out during the coffee harvesting process, so it can be said that the predictions generated are reliable.

The ROC curve shows the true positive rate (TPR) versus the false positive rate (FPR) calculated by the Fine Tree. The true positive rate that are in the range of 0 to 1, and the AUC values being the largest correspond to the percentage correctly performed of the positive class observations, therefore, they indicate a better performance of the trained model in recognizing the activities. made during the coffee harvesting process.

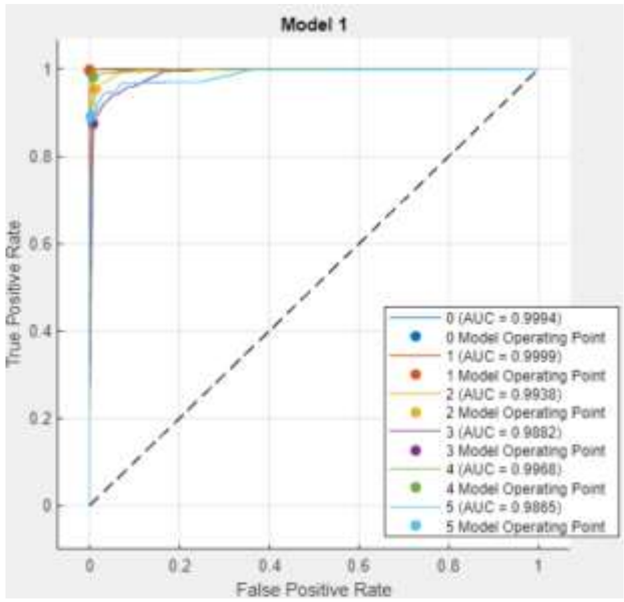


**Figure 18** ROC Curve

## Financing

Financing: This work has been funded by CONACYT [scholarship number: 830166,2022]

## Conclusions

The artificial intelligence model gives an accuracy of 97.1%, so the model has characteristics of greater predictive power to classify activities reliably, so it can be said that Artificial Intelligence models make automatic learning possible by carrying out carry out efficient computational processes for the recognition of human activities in different areas of interest.

These capabilities provide new opportunities to improve the efficiency and accuracy of signal processing, which can have a significant impact in various areas and industries that require advanced signal processing and analysis.

**References**

Golden, R. M. (2020). Formal Machine Learning Algorithms. In Statistical Machine Learning. https://doi.org/10.1201/9781351051507-3

Sangwan, A., & Bhattacharya, P. P. (2015). Wireless Body Sensor Networks: A Review. International Journal of Hybrid Information Technology, 8(9), 105–120. https://doi.org/10.14257/ijhit.2015.8.9.12

Lai, X., Liu, Q., Wei, X., Wang, W., Zhou, G., & Han, G. (2013). A survey of body sensor networks. In Sensors (Switzerland) (Vol. 13, Issue 5). https://doi.org/10.3390/s130505406

Dreiseitl, S., & Ohno-Machado, L. (2002). Logistic regression and artificial neural network classification models: A methodology review. Journal of Biomedical Informatics, 35(5–6), 352–359. https://doi.org/10.1016/S1532-0464(03)00034-0

F. John Dian, R. Vahidnia and A. Rahmati, "Wearables and the Internet of Things (IoT), Applications, Opportunities, and Challenges: A Survey," in IEEE Access, vol. 8, pp. 69200-69211, 2020, https://doi.org/10.1109/ACCESS.2020.2986329

Lee, S. M., & Lee, D. H. (2020). Healthcare wearable devices: an analysis of key factors for continuous use intention. Service Business, 14(4), 503–531. https://doi.org/10.1007/s11628-020-00428-3

Shalev-Shwartz, S., & Ben-David, S. (2013). Understanding machine learning: From theory to algorithms. In Understanding Machine Learning: From Theory to Algorithms (Vol. 9781107057). https://doi.org/10.1017/CBO9781107298019

Aroganam G, Manivannan N, Harrison D. Review on Wearable Technology Sensors Used in Consumer Sport Applications. Sensors (Basel). 2019 Apr 28;19(9):1983.https://doi.org/10.3390/s19091983

McClure, K., Erdreich, B., Bates, J. H. T., McGinnis, R. S., Masquelin, A., & Wshah, S. (2020). Classification and detection of breathing patterns with wearable sensors and deep learning. Sensors (Switzerland), 20(22), 1–13. https://doi.org/10.3390/s20226481

Sattar, F., Azad, A. A. M., Sikder, M. S., & Arefin, M. S. (2019). Body sensor networks for monitoring performances in sports: A brief overview and some new thoughts. Artificial Intelligence Research, 8(1), 25. https://doi.org/10.5430/air.v8n1p25

Chen, F. (2021). Athlete muscle measurement and exercise data monitoring based on embedded system and wearable devices. Microprocessors and Microsystems, 82(December 2020), 103901.https://doi.org/10.1016/j.micpro.2021.103901