

UNIVERSIDAD POLITÉCNICA DE MADRID
Escuela Técnica Superior de Ingenieros de Telecomunicación



**Contribution to Methodologies for
Human Activity Recognition: Focusing
on the Visually Impaired**

DOCTORAL THESIS

Submitted for the degree of Doctor by:

Milagros Quilimara Jaén Vargas
Master in Project Management

Madrid, 2024



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Doctoral Degree in Biomedical Engineering

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To my beloved brother.

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Abstract

The growing number of visually impaired individuals (VIPs) worldwide, representing approximately 2.2 billion of the global population, has led to increased interest in the development of assistive technologies. These technologies aim to enhance mobility and safety in indoor and outdoor environments, preventing obstacles and providing support to rehabilitation professionals in addressing biomechanical constraints, such as gait, posture, and balance.

Conversely, the advent of technologies such as artificial intelligence (AI) and the utilization of wearable devices to gather data on human movement are pivotal for the advancement of solutions that can assist and enhance the quality of life for individuals with visual impairments (VIPs). For instance, scientists have developed algorithms for human activity recognition (HAR) that enable the automatic extraction of features. These algorithms utilize inertial sensors as input data.

For this reason, the Bioinstrumentation and Nanomedicine Laboratory (LBN) of Universidad Politécnica de Madrid (UPM) is engaged in the development of methodologies for human activity recognition, with a particular focus on the visually impaired.

In particular, we proposed a study to determine the optimal balance assessment for VIP. We considered the data acquisition device (OpenSense RT), selected the appropriate Deep Learning techniques to treat time series data, developed a personalized balance test for VIP (mini-BESTest), and tested various machine learning and deep learning models to identify differences in balance between sighted and blind individuals.

Prior to utilizing IMU data, an assessment was conducted on the mini-BESTest evaluation table. The application of K-Means clustering revealed that Test 3, which involves standing on one leg, is a reliable indicator of the distinction between sighted and blind individuals. On the other hand, the study tested a number of AI model architectures for time series data, with the hybrid CNN-LSTM option 2 emerging as the most effective in multiclass classification. The models, such as LSTM and GRU, exhibited a longer latency in their predictions. The manner in which data is presented is of crucial importance in the context of AI training. Methodology 2, which considers each leg separately, was found to be the most effective. The use of acceleration data with a sliding window of 25 resulted in an

accuracy of 80% and an F1-score of 61%. The discussion about the optimal sliding window size revealed that halving the IMU acquisition frequency (from 50 Hz to 25 Hz) similar performance metrics. The raw acceleration data indicated comparable performance to quaternions, although the latter increased the computational complexity.

Key words

Accelerometer, quaternions, Deep learning, Human activity recognition, Sliding windows, Motion capture.

Resumen

El creciente número de personas con discapacidad visual en todo el mundo, que representan aproximadamente 2.2 billones de la población mundial, ha suscitado un mayor interés por el desarrollo de tecnologías de asistencia. El objetivo de estas tecnologías es mejorar la movilidad y la seguridad en entornos interiores y exteriores, evitando obstáculos y prestando apoyo a los profesionales de la rehabilitación a la hora de abordar limitaciones biomecánicas, como la marcha, la postura y el equilibrio.

A la inversa, la llegada de tecnologías como la inteligencia artificial (IA) y la utilización de dispositivos portátiles para recopilar datos sobre el movimiento humano son fundamentales para el avance de soluciones que puedan ayudar y mejorar la calidad de vida de las personas con discapacidad visual. Por ejemplo, los científicos han desarrollado algoritmos para el reconocimiento de la actividad humana (HAR) que permiten la extracción automática de características. Estos algoritmos utilizan sensores inerciales como datos de entrada.

Por este motivo, el Laboratorio de Bioinstrumentación y Nanomedicina (LBN) de la Universidad Politécnica de Madrid (UPM) está inmerso en la creación de una contribución a las metodologías para el reconocimiento de la actividad humana, con un enfoque particular en las personas con discapacidad visual.

En concreto, propusimos un estudio para determinar la evaluación óptima del equilibrio para VIP. Consideramos el dispositivo de adquisición de datos (OpenSense RT), seleccionamos las técnicas de aprendizaje profundo para tratar los datos de series temporales, desarrollamos una prueba de equilibrio personalizada para VIP (mini-BESTest) y probamos varios modelos de aprendizaje automático y aprendizaje profundo para identificar diferencias en el equilibrio entre individuos videntes y ciegos.

Antes de utilizar los datos de la IMU, se realizó una evaluación en la tabla de evaluación del mini-BESTest. La aplicación de la agrupación de K-Means reveló que la prueba 3, que consiste en ponerse de pie sobre una pierna, es un indicador fiable de la distinción entre personas videntes y ciegas. Por otro lado, el estudio puso a prueba varias arquitecturas de modelos de IA para datos de series temporales, y la opción 2, la CNN-LSTM híbrida, resultó ser la más eficaz en la clasificación multiclase. Los modelos como LSTM y GRU mostraron una mayor latencia en sus predicciones. La forma en que se presentan los datos es de crucial

importancia en el contexto del entrenamiento de IA. La metodología 2, que considera cada pierna por separado, resultó ser la más eficaz. El uso de datos de aceleración con una ventana deslizante de 25 dio como resultado una precisión del 80% y una puntuación F1 del 61%. El debate sobre el tamaño óptimo de la ventana deslizante reveló que la reducción a la mitad de la frecuencia de adquisición de la IMU (de 50 Hz a 25 Hz) ofrecía métricas de rendimiento similares. Los datos brutos de aceleración indicaban un rendimiento comparable al de los cuaterniones, aunque este último aumentaba la complejidad computacional.

Palabras clave

Acelerómetro, cuaterniones, Deep learning, Reconocimiento de actividad humana, Ventanas deslizantes, Captura de movimiento.

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Abbreviations and Acronyms

UPM	Universidad Politécnica de Madrid
IMU	Inertial Measurement Unit
MOCAP	Motion Capture Systems
AR	Augmented Reality
VR	Virtual Reality
ML	Machine Learning
DL	Deep Learning
DNN	Deep Neural Network
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
CNN-LSTM	Hybrid model: CNN + LSTM
mini-BESTest	mini-Balance Evaluation System Test
LOOV	Leave-One-Out Cross-Validation

Chapter 1. Introduction

1.1 Reference Framework / Motivation

Nowadays the loss of vision is not only a concern for children who are born with this condition but is also affecting people in their middle to old ages, approximately after the age of 50.

The World Health Organization (WHO) has recently published data indicating that, worldwide, approximately 2.2 billion individuals suffer from some form of visual impairment [1]. In Spain, the prevalence of visual impairment is estimated to be 2.14% of the population, 920.900 have low vision and 58.300 are blind¹. Additionally, it has been established that a number of conditions, including uncorrected refractive errors, cataracts, age-related macular degeneration, glaucoma, diabetic retinopathy, corneal opacity, and trachoma, can lead to visual impairment. In Latin America, the prevalence of blindness ranges from 1.1% to 4.1% of the population [2]. In Panama, 10.2% of the blind population is attributable to glaucoma [3]. Despite the implementation of policies aimed at preventing visual impairments, such as the 2014-2019 plan and Vision 2020, a significant proportion of the global population continues to suffer from this disability.

Visual impaired people (VIP) require mechanisms to assist in important areas such as orientation and mobility (O&M) and rehabilitation, in order to regain autonomy, which may be affected due to the lack of vision. It is also important to recover the physical activity (PA) of VIPs, as in some cases they have registered a lack of engagement in activities due to a feeling of less independence.

The literature demonstrates the existence of a wide range of assistive technologies developed for VIPs. Some of them are for developing aids for orientation in indoor or outdoor spaces (guiding and navigation apps), others are for avoiding obstacles (object detection systems), and still others are for studying gait with and without the cane and also posture (biomechanical-rehabilitation apps). All of these solutions are created to improve VIP quality of life (QoL) and to make daily life easier, especially when it comes to performance activities of daily living (ADL).

¹ Ópticos Optometristas de Galicia. Notas de Prensa. Available online: [opticosoptometristasdegalicia](https://www.opticosoptometristasdegalicia.es/) (accessed January 2024).

The emergence of technologies such as Artificial Intelligence (AI) and the use of wearable devices to acquire data when people move are crucial for the development of solutions that can assist and enhance the quality of life for VIPs. For instance, scientists have developed algorithms of human activity recognition (HAR) that enable the automatic extraction of features [4], [5]. Those algorithms use inertial sensors as input data [6], [7].

In light of the aforementioned considerations, the Bioinstrumentation and Nanomedicine Laboratory (LBN) of Universidad Politécnica de Madrid (UPM) is engaged in the development of assistive technologies for individuals with visual impairments. In this context, we have followed the creation and testing of methodologies to assist in the orientation, mobility, and rehabilitation of individuals with visual impairments.

1.2 Problem Statement

Firstly, as previously stated, individuals with VIPs require autonomy and confidence recovery. This is essential for enhanced quality of life (QoL) in activities of daily living (ADL), at work, and during sports.

Secondly, another crucial need is the necessity for increased research, particularly in the field of rehabilitation, which should include gait, posture, and balance in VIPs.

This work arises from the necessity of incorporating aids for rehabilitation and biomechanical analysis in VIPs. For this reason, we propose the integration of artificial intelligence as a method to analyze data and the use of wearable devices such as inertial measurement units (IMUs) and motion capture systems (MOCAPs) for acquiring data.

In essence, the primary objective of this study is to devise methodologies for human activity recognition (HAR). These methodologies will be employed to assess the balance of individuals with visual impairments, with the intention of providing additional rehabilitation tools. This proposal, which is enhanced by the use of inertial sensors as data capture devices during activity execution, has the potential to extend into the field of rehabilitation.

1.3 Thesis Outline

This thesis is structured in nine chapters, which outlined below:

The first chapter illustrates the motivation of this study, the problem to be addressed and the research methodology employed.

The second chapter provides an overview of the state-of-the-art surrounding the study. The concepts of the two dispositive for acquiring data are mentioned, as well as the tools for data analysis used, we talk about Artificial Intelligence and Deep Learning most used architectures for time series data, and the applications using IMUs and Artificial Intelligence.

The third chapter explains the hypothesis and objectives of this thesis.

The fourth chapter describes the methodology we followed where developing and testing.

The fifth chapter presents the results, and its discussion is in chapter sixth.

Conclusions are in chapter seventh and feature lines in chapter eighth.

Finally, a scientific contribution is listed in chapter ninth.

Chapter 2. State of the Art

This chapter discusses the state of the art of this thesis. The main goal of this chapter is to provide an overview of the devices and methodologies utilized in the development of assistive technologies for individuals with disabilities. Initially, the distinction between IMUs and MOCAP as data acquisition systems is discussed, followed by an explanation of the analytical tools necessary to process the data prior to its input into artificial intelligence models for human activity recognition.

2.1 Systems for Collecting Data from Human Body Movements.

Wearables are devices that track information when a subject is moving. There are several types of wearables, but those that are the focus of this thesis are those that use an Inertial Measurement Unit (IMU) and a Motion Capture System (MOCAP) to record the data.

2.1.1 Inertial Measurement Unit

First, IMUs are composed by three types or sensors: accelerometers to measure planar (biaxial) or 3D movement (triaxial); gyroscopes to measure rotation and magnetometers to measure relative position and can improve the reading of gyroscope. Mainly, IMUs are presented by a combination of two sensors type:

- a) accelerometer and gyroscope
- b) accelerometer, gyroscope, and magnetometer.

Regarding type a, acceleration values obtained from accelerometer and angular velocity from gyroscope are kept separately. Angles can be measured from both sensors, thus both data can be calibrated as shown in Figure 2-1 (1) to get more accurate output data.

This can have from 2 or 3 DOF (Degrees of Freedom) until 4 or 6 DOF depending on it combining both sensors. It is important to clarify that a degree of freedom (DOF) determines the number of independent parameters in a system [8], in other words how many axes the sensor will measure.

Type b is good for dynamic orientation because adding magnetometer is measured yaw angle rotation and can be calibrated to gyroscope data to improve drift issues and is shown Figure 2-1 (2).

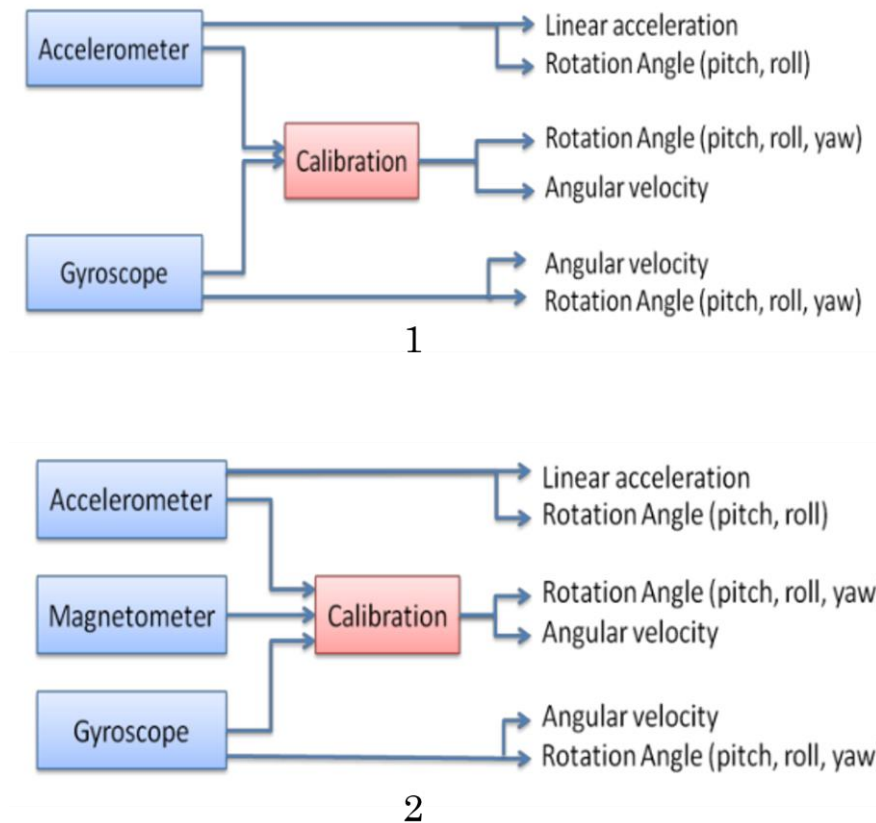


Figure 2-1. (1) IMU based on two types of sensors. (2) IMU based on three types of sensors. Credits:²

Table 2-1 presents a comparison of the characteristics of IMUs according to their role in the context of three signal inputs: only acceleration; Acc + Gyro; and Acc + Gyro + Mag. The principal approach to the findings was sensor fusion of accelerometers, gyroscopes, and magnetometers (35%), while the less common approach to the findings was the use of gyroscope input (10%). According to the role of the IMUs, three fields can be identified: motion measurement, angular velocity, and fall detection; orientation/attitude estimation and heading; and positioning and tracking.

² N. Ahmad, R. A. R. Ghazilla, N. M. Khairi, and V. Kasi, "Reviews on Various Inertial Measurement Unit (IMU) Sensor Applications," *International Journal of Signal Processing Systems*, pp. 256–262, 2013, doi: 10.12720/ijsp.1.2.256-262.

Table 2-1. IMU types depend on signal input.

Data type	Role	IMU	Sensor fusion	Reference
Acceleration	Identify human movement	ADXL345	RGB Camera, Ultrasonic Sensor	[9]
Acceleration	Measures physical activity	ActiGraph GT3x	N/A	[10]
Acceleration	Measures physical activity	ActiGraph wGT3X-BT	N/A	[11]
Acceleration	Measures physical activity	ActiGraph wGT3X-BT	N/A	[12]
Acceleration	Measures physical activity	ActiGraph wGT3x+	N/A	[13]
Acceleration	Sense the foot movements	KXR94-2050	N/A	[14]
Acceleration	Measures physical activity	ActiGraph GT3x	N/A	[15]
Acceleration	Measures physical activity	ActiGraph GT3x	N/A	[16]
Acceleration	Monitoring of human activities	Not specified	N/A	[17]
Gyroscope	Measure the tilt angle	MPU-6050	Ultrasonic sensor, GPS	[18]
Gyroscope	Measure the tilt angle	MPU-6050	Ultrasonic sensor, GPS	[19]
Gyroscope	Track the direction of	Smartphone	Camera	[20]

	gravity, orientation			
Gyroscope	Sweeping velocity	Re Sense	Camera	[21]
	IMU			
Acc + Gyro	Pedestrian dead reckoning	MPU-6050	RGB-D camera, GPS	[22]
Acc + Gyro	Motion detection	MPU-6050	RGB camera, ultrasonic sensor	[23]
Acc + Gyro	Position estimation and orientation	MPU-6050	CMOS camera, line laser	[24]
Acc + Gyro	Fall detection and attitude estimation	Not specified	RGB-D camera, GPS, velocity sensor	[25]
Acc + Gyro	Fall detection	Smartphone IMU	Ultrasonic sensor, GPS	[26]
Acc + Gyro	Orientation	MPU-6050	GPS, ultrasonic, and wet floor sensors	[27]
Acc + Gyro	Attitude estimation	Not specified	RGB-D camera	[28]
Acc + Gyro	Step counting	Not specified	Ultrasonic sensor, GPS	[29]
Acc + Gyro	Orientation and Height estimation	Not specified	RGB-D camera	[30]
Acc + Gyro	Heading estimation	Not specified	GPS, compass	[31]
Acc + Gyro	Angular velocity and acceleration	Smartphone IMU	Strain gauges	[32]
Acc + Gyro	Pose estimation	LSM9DS1	RGB-D camera	[33]

Acc + Gyro	Orientation of the head and hand	BMI055 Bosch	UWB FMCW radar sensor	[34]
Acc + Gyro + Mag	Device and pose estimation	VN-100 IMU/AHRS	RGB-D Camera	[35]
Acc + Gyro + Mag	Step counting, body orientation	Smartphone IMU	Barometer	[36]
Acc + Gyro + Mag	Attitude estimation and orientation	Smartphone IMU	Beacons, GPS	[37]
Acc + Gyro + Mag	Pedestrian dead reckoning	Smartphone IMU	Beacons	[38]
Acc + Gyro + Mag	Body orientation	BNO-055	Optical flow sensors, UWB	[39]
Acc + Gyro + Mag	Path calculation	Not specified	RGB camera, ultrasonic sensor	[40]
Acc + Gyro + Mag	Acceleration and angular rate	Xsens IMU	RGB camera, line laser	[41]
Acc + Gyro + Mag	Tracking the head and body movement	LPMS-CURS2	RGB camera, structure sensor PS1080	[42]
Acc + Gyro + Mag	Detect the right edge of the road	Smartphone IMU	RGB-D camera, GPS	[43]
Acc + Gyro + Mag	Step counting and Heading estimation	MPU-9250	Ultrasonic sensor, Pi Camera	[44]
Acc + Gyro + Mag	Head tracking	MPU-9250	GPS / GLONASS and UWB	[45]
Acc + Gyro + Mag	Positioning and step size estimation	Smartphone IMU	N/A	[46]
Acc + Gyro + Mag	Pose estimation	VN 100 IMU/AHRS	RGB-D camera	[47]

Acc + Gyro + Mag	Absolute orientation	Smartphone IMU	RGB-D camera	[48]
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Furthermore, a variety of manufacturers offer IMUs on the market, including Xsens, ActiGraph, mbientlab, and Shimmer. Figure 2-2 depicts the price range of each manufacturer.

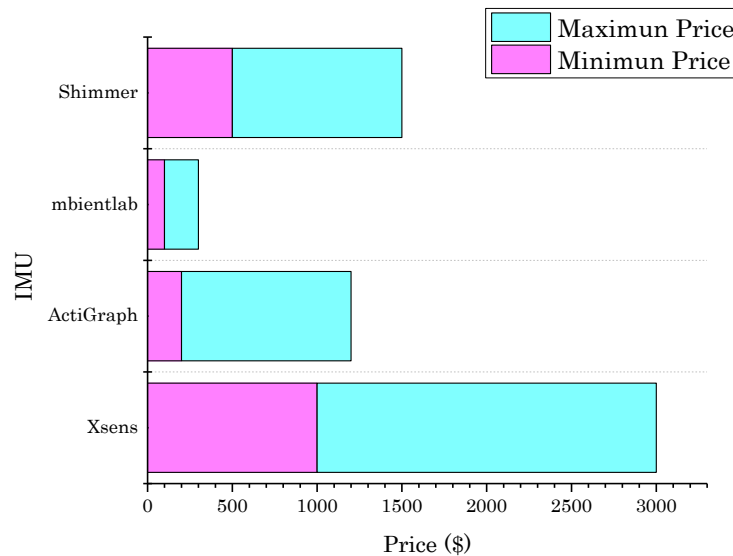


Figure 2-2. IMU's range of price per fabricant.

When selecting the IMUs to be utilized in this study, the decision was based on the price range, the ease with which an app could collect the data, and the ease with which the data could be obtained. The decision was made to select the mbientlab sensors, particularly the MetamotionR (MBIENTLAB INC, San Francisco, CA., USA) as illustrated in Figure 2-3-(1), due to their accessibility displayed in Figure 2-3-(2) with the MetaBase app, and the sensor's cost-effectiveness.

As previously stated, an IMU is a device that measures a change in the space (x, y, z) when an object is in motion. The accelerations and gyroscope components permit the acquisition of quaternions and Euler angles, which serve as orientation measures.

2.1.1.1 Quaternions and Euler Angles

Quaternions and Euler angles are useful for understanding human poses, as they facilitate the orientation in 3D of a point in space. This lets us know which joints are being used for body orientation.

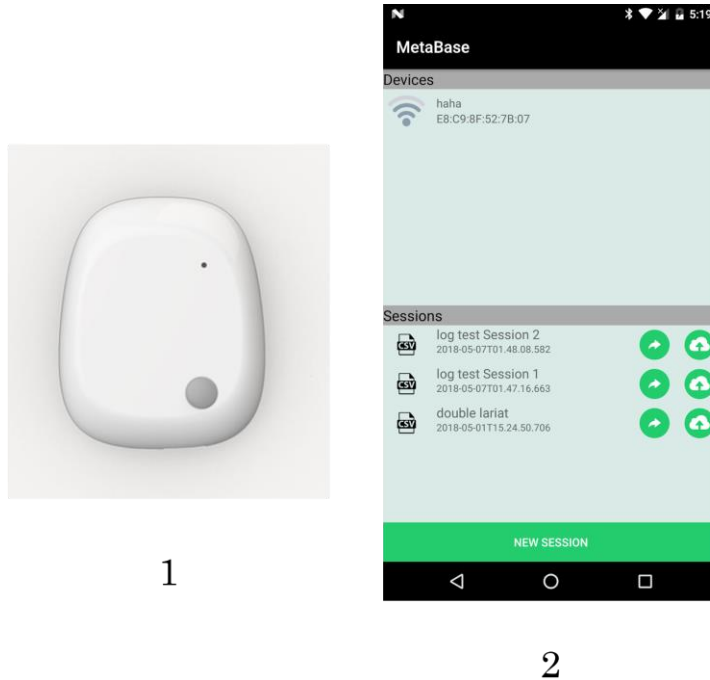


Figure 2-3. (1) IMU sensor – MetamotionR. (2) MetaBase app.

It is crucial to comprehend the representation of quaternions in a plane and the methodology for their calculation. Fundamentally, quaternions are four numbers that facilitate the rotation of a point in three-dimensional space. These numbers adhere to the following configuration: a real and an imaginary part.

The angles that are formed when a body rotates are known as Euler angles. As complex numbers possess a two-dimensional extension of the real numbers, quaternions are four-dimensional extension of complex numbers. For instance, complex numbers are $2+i$, quaternions are $2+4i+1j+2k$. For instance, a Real part + $i+j+k$. It basically refers to an upgrade in a complex plane (Real+ i) to know a rotation in 2D.

Back in time, mathematics started working with real numbers. Passing the years, complex numbers were created adding an imaginary (i) part to the number, resulting in a 1D representation. After that, to represent a number in the 2D plane

the axis (j) which is perpendicular to the other axis was. With this axis the rotation was possible to be observed. In 1843, Sir William Rowan Hamilton found the importance of multiplying complex numbers to obtain a representation of orientation in 3D and discovered that he named quaternions. He added one axis more (k) which is perpendicular to all the rest, and the real part is moving to get the rotations. All these representations are in Figure 2-4.

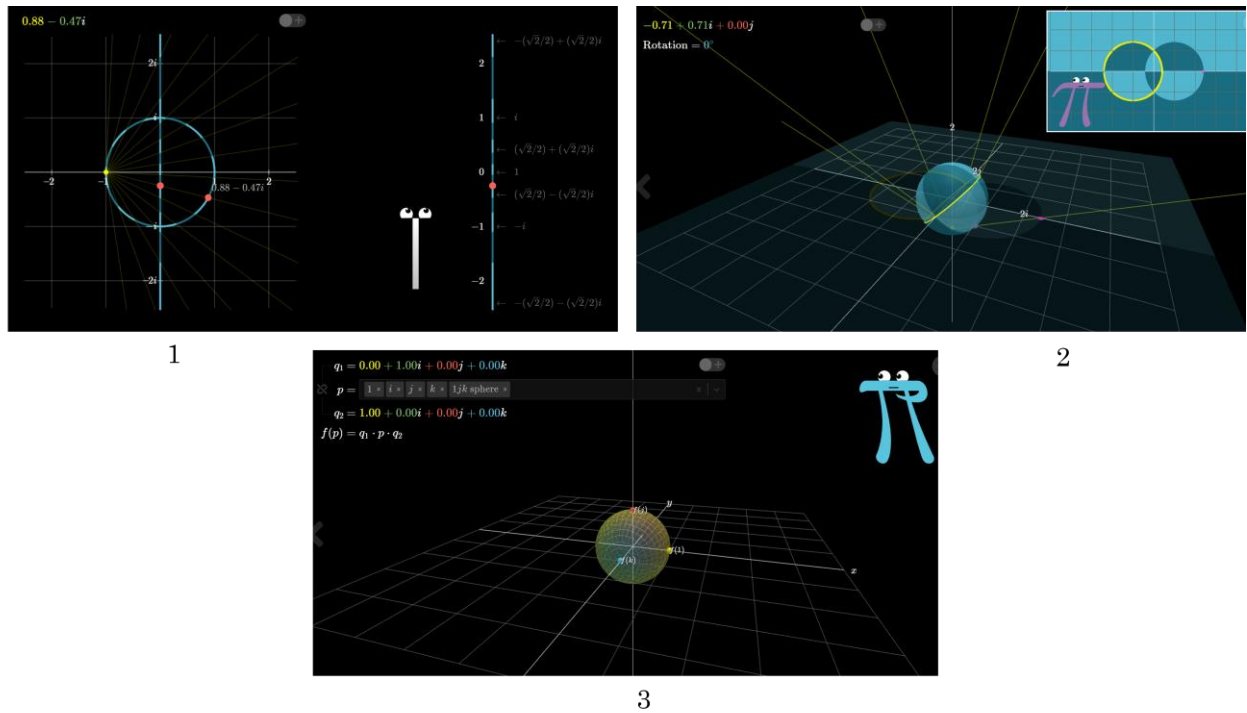


Figure 2-4. Rotation in (1) 2D. (2) 3D. (3) 4D. Credits: ³

For those seeking to gain more information about the orientation or attitude of a point, it is important to note that the use of quaternions and Euler angles can be a valuable tool in computing the quaternions matrices. However, it is not uncommon for a gimbal error to occur.

The rotation about the x-axis is equivalent to the roll angle, denoted by α . Similarly, the rotation about the y-axis is equivalent to the pitch angle, denoted by β . Finally, the rotation about the z-axis is equivalent to the yaw angle, denoted by γ .

³ Ben Eater Website. Visualizing quaternions. Available online: <https://eater.net/quaternions> (accessed February 2024).

Once the reader is familiar with the concepts of quaternions and Euler angles and their relevance to attitude, it is important to understand how to obtain quaternions from IMU data. As the IMU contains an accelerometer, gyroscope and, in some cases, a magnetometer, quaternions can be derived through the use of a Mahony filter, which is a nonlinear complementary filter on the special linear group [49]. This filter is employed to obtain quaternions from the readings of the accelerometer and gyroscope, which represent the data provided by a 6DOF IMU.

Moreover, a specific complementary filter for attitude estimation of a fixed-wing unmanned aerial vehicle (UAV) has been identified in the literature. The filter combines accelerometer output for low-frequency estimation with integrated gyrometer output for high-frequency estimation. This filter is designated the Explicit Complementary Filter (ECF) and incorporates a model of the longitudinal angle-of-attack dynamics of a fixed-wing aircraft [50].

2.1.2 MOCAP System

Motion Capture System (MOCAP) is an optical system that mainly uses a high-speed camera to capture the spatial position of reflective markers on the surface of a human body to reconstruct the spatial posture of a human body as its shown in Figure 2-5. This method is able to guarantee the accuracy, consequently, is usually called the gold standard in this field [51]. In this case, the information provided by MOCAP corresponds to the triaxial position of a marker in the space, in other words the position in x, y and z. Besides, for obtaining velocity and acceleration the position is derivated one and two times, respectively.

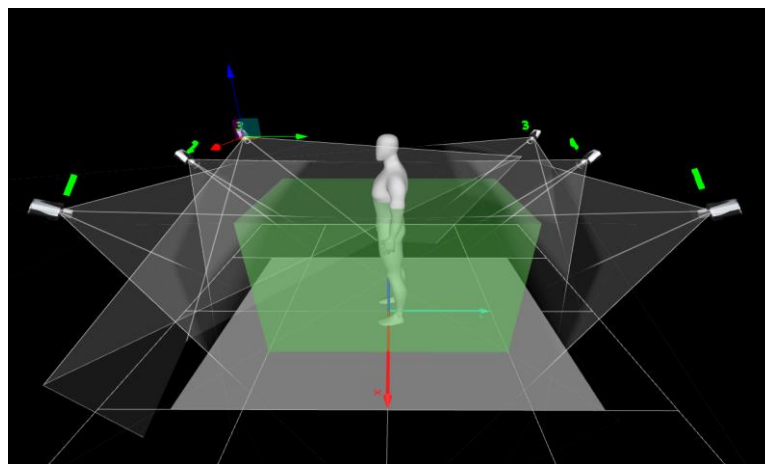


Figure 2-5. MOCAP system.

The system works as follows: the cameras record the trajectory of the markers during an activity, after which the recorded information is processed in a dedicated software. This software displays the markers on a skeleton and locates their positions as displayed in Figure 2-6, which corresponds to Qualisys Track Manager (QTM) interface.

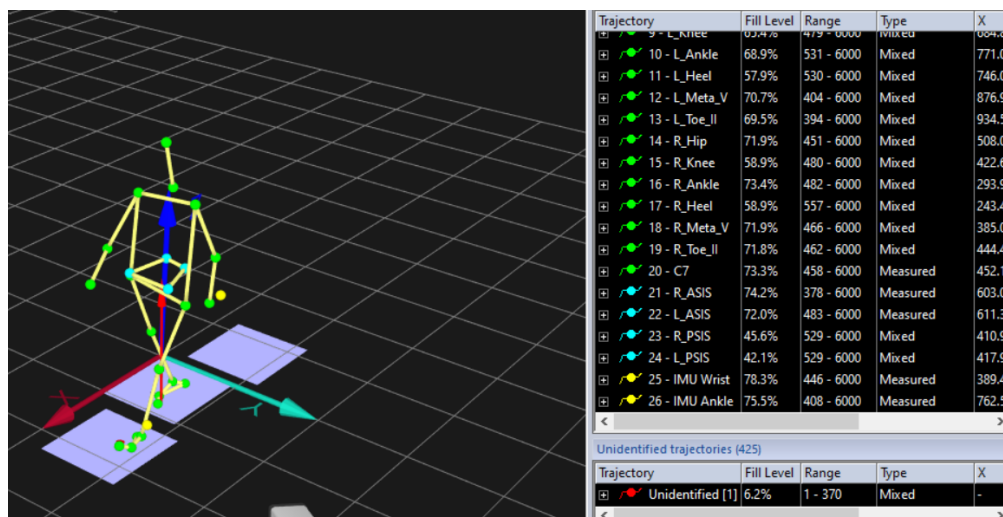


Figure 2-6. Qualisys Track Manager (QTM) - Software.

In addition, the most commonly used MOCAP systems for movement analysis are: Vicon (Vicon©, Oxford, United Kingdom), Qualisys (Qualisys©, Göteborg, Sweden), Optitrack (OptiTrack©, Corvallis, Oregon, USA), Xsens (Xsens©, Enschede, Netherlands), and others.

Although, as mentioned above, MOCAP is considered the gold standard for motion analysis, the implementation of IMUs as a data acquisition system is growing due to its low-cost characteristic.

In this thesis we used the Qualisys MOCAP system as motion analysis tool. The study methodology is explained in Section Real-time Indoor Human Activity Positioning using IMU Data and DL Algorithms.

2.2 Tools for Treating Data

Once data collection is complete, it is necessary to consider the tools that can be used to treat the data. There are various methods for analyzing data before the use of Artificial Intelligence.

2.2.1 Data Analysis

Before training the model, it is important to preprocess the data to feed it. Literature mentions the uses of filtering, feature selection techniques and labelling.

2.2.1.1 Data Pre-processing

The first key to working properly with AI is how to accommodate the data to feed the AI models. There are several methods to preprocess the data. The most common are data cleaning, data integration, data reduction and data transformation⁴.

- **Data Cleaning:** To clean the dataset is necessary to verify incorrect, incomplete, and missing values. For instance, the Not a Number (Nan's) are typical to search because if there are only numbers in a column, though finding Nan's automatically check some characters that were added by mistake and then replace it with correct value.
- **Data Integration:** To combine multiple data sources into a big one.
- **Data Reduction:** to reduce the data volume to make easy analysis and get almost the same results.
- **Data Transformation:** Include changes in the data structure. The most used methods are smoothing, aggregation, discretization, and normalization.
- **Smoothing:** To remove noise in the data in order to see a change in the prediction.
- **Aggregation:** The data is shown in a summary and gets an analysis description.
- **Discretization:** The data can be reduced or split into intervals.
- **Normalization:** A dataset is normalized when scaling the data in order to be represented in a smaller range. For instance, ranging from -1.0 to 1.0.

⁴ Analytics Vidhya Website. Data Preprocessing in Data Mining: A Hands-on Guide. Available online: <https://www.analyticsvidhya.com/blog/2021/08/data-preprocessing-in-data-mining-a-hands-on-guide> (accessed February 2024).

2.2.1.2 Data Filtering

The application of a filtering technique to data represents a strategy for the reduction of noise in the signal [52]. There are various types of filters to apply on the signal. The most used for this type of data are: Magdwick, Kalman, Butterworth

2.2.1.3 Sliding Window

The sliding window technique is utilized for analyzing sequential data, such as time series, text data, or images. Time Series Analysis aims to detect patterns, trends, or anomalies in time-series data, such as stock prices, sensor readings, or weather data. In Text Processing, it extracts features or performs analysis on text data, such as sentiment analysis, named entity recognition, or text classification. In Image Processing, filters and feature extraction algorithms are applied to analyze images. These include edge detection, object recognition, and texture analysis.

There are two main ways to create sliding windows, those based on dividing the sequence following a time in seconds and those based on working with the samples (frames) of the sequence. Moreover, windows can be classified into two types: fixed or adaptive; and overlapping and non-overlapping. Windows are defined as fixed when they have the same size during the whole sequence; on another hand, they are adaptive if their size changes depending on special criteria when a movement occurs. Besides, windows are overlapped when the next window stays as part of the last sequence, in other words, an overlap occurs between adjacent windows; on the contrary, it is named non-overlapping windows [53], [54].

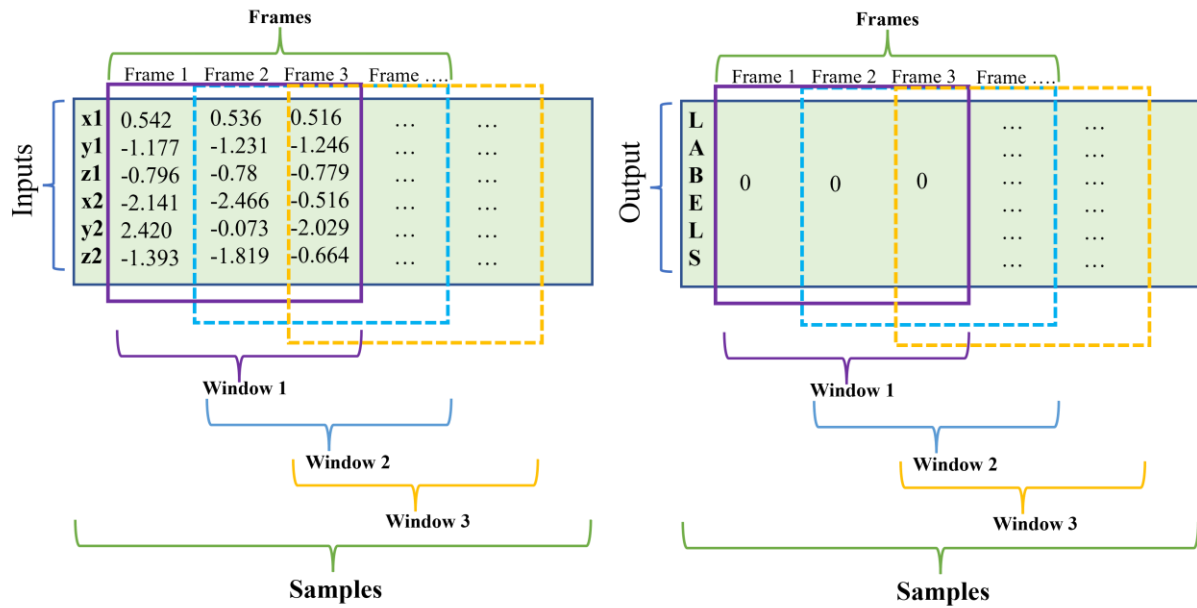


Figure 2-7. Sliding window schematic.

A sliding window comprises three elements: samples, number of time steps (window size), and features (inputs). First, a sequence is a broader sample in which there may be one or more singular samples; second, time steps or what we denominated “window size” corresponds to one observation in the sequence which may be included one or more frames; and third, a feature is the input of the sequence and corresponds to one observation as a time step. (See Figure 2-7). When the window slides throughout the samples, a new phase is created.

2.2.1.4 Data Labelling

The process of data labelling is important when attempting to classify data accurately using Deep Learning (DL) [55]. This technique involves the labeling of data in order to differentiate between various categories, such as which part of the data belongs to any given activity. The manner in which this is done can be either automatic or manual, depending on the specific application in question. This distinction is particularly relevant in the context of real-time applications, where the need for manual intervention may be less pronounced.

2.2.2 Artificial Intelligence

Artificial Intelligence (AI) processes significant amounts of data to efficiently learn from information provided in this case by IMUs and MOCAP signals and predict things. AI is divided into Machine Learning and Deep Learning.

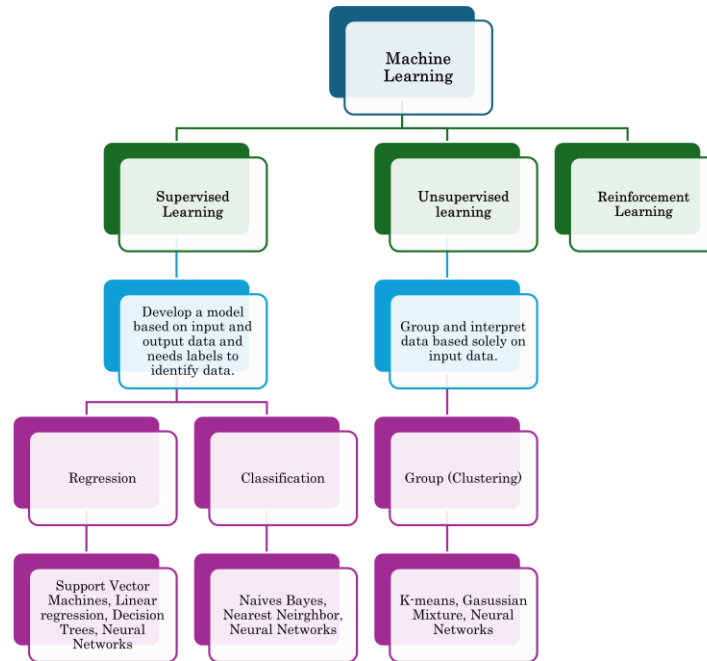


Figure 2-8. Machine Learning schematic.

Machine learning (ML) is the ability of systems to learn from specific data to automate the process of building analytical models and solve related tasks [56]. Deep learning (DL) is a subset of machine learning (ML) that can automatically learn representations from data [57], eliminating the need for manual feature extraction by data analysts. This approach has shown impressive results in domains such as image recognition, natural language processing, and speech recognition.

In addition, Machine Learning involves three types of problems: supervised, unsupervised and reinforcement learning as shown in Figure 2-8. A problem is considered supervised when the output is known, while it is unsupervised when the output is unknown. In supervised learning, labeled examples are used to train the model, while in unsupervised learning, the model learns from unlabeled data. Additionally, Reinforcement Learning (RL) is when an agent learns by interacting with an environment through the gathering of experience [58].

2.2.3 Machine Learning

The techniques that will be employed in this study in accordance with the principles of ML are Feature selection and Clustering.

2.2.3.1 Feature Selection

Feature selection is a technique that identifies a subset of the most relevant features (columns) for a given dataset.

In this thesis, we employed the Recursive Feature Elimination (RFE) which is a technique employed in machine learning, particularly in supervised learning tasks such as classification or regression. The RFE algorithm operates by initially identifying all features within the training dataset and then iteratively eliminating those that are deemed to be least important until a specified number of features remains. This is accomplished by fitting the specified machine learning algorithm, which serves as the core of the model, ranking the features according to their relative importance, discarding the least important features, and re-fitting the model. This process is repeated until a specified number of features remains. When the desired number of features has been reached, the process is complete [59].

2.2.3.2 Clustering

Clustering is a fundamental technique in Machine Learning. It basically organized a bunch of data into groups or clusters. The data is characterized by the greatest similarity within the same cluster and the greatest dissimilarity between different clusters [60].

Additionally, as an unsupervised learning technique, clustering aims to identify inherent structures or patterns in datasets without the need to label the results.

The most used clusters algorithms are hierarchical, K-Means, DBSCAN (Density-Based Spatial Clustering of Applications with Noise), and mean shift.

2.2.3.2.1 K-Means

K-Means algorithm partitioning set of data into clusters k as shown in Figure 2-9. It is a distance-based clustering algorithm that divides data into a number of clusters in numerical attributes [61].

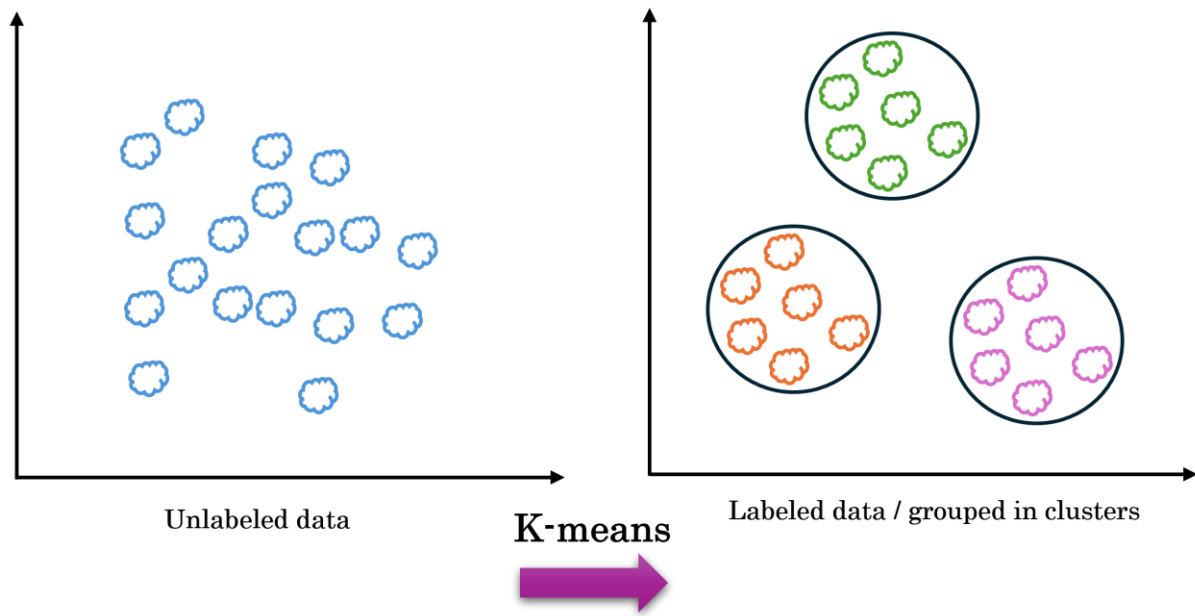


Figure 2-9. K-means clustering algorithm.

2.2.3.2.2 The Elbow Method

The Elbow method is a widely used technique in clustering analysis. Its purpose is to determine the optimal number of clusters (k) in a dataset.

This method involves plotting the sum of squared distances between data points and their associated cluster centroids for different values of k . The point where the rate of decrease of the sum of squares changes is identified, creating an elbow shape. The combination of the elbow and K-means methods can be employed to identify the optimal value of k , which represents the most effective cluster.

In this thesis, both methods were utilized.

2.2.3.2.3 Clustering Quality and Performance Metrics

Additionally, the literature offers additional insights into clustering quality and performance, suggesting alternative methods to complement the Elbows method.

A quality index is a criterion that enables the selection of an appropriate clustering method, the determination of an optimal number of clusters, and the evaluation or development of a new method [62]. The most utilized quality indexes are Silhouette, Calinski-Harabasz [63], Davis-Bouldin [64], and Within-Cluster Sum of Squares.

- The Silhouette index is a value that can range from -1 to 1. A value close to 1 indicates that the points are well-clustered, while a value close to -1

indicates that the points are poorly clustered. A value close to 0 indicates cluster overlap.

- The Calinski-Harabasz index is a measure of the separation between clusters and the compactness within clusters. Higher values indicate better separation between clusters. The measure assesses the average similarity between each cluster and its most similar neighboring cluster. Lower values indicate a more optimal partitioning of the data set.
- The Davis-Bouldin index is a quantitative measure of the compactness and separation between clusters in a dataset. The index is designed to identify clusters with high intra-cluster similarity and low inter-cluster similarity, resulting in a low index value, which indicates a more optimal clustering structure. A lower Davis-Bouldin index is indicative of a superior clustering structure.
- The Within-Cluster Sum of Squares (WCSS) is a statistical measure that indicates the compactness and density of clusters. A lower value of WCSS is generally considered to be indicative of superior clustering.

Among the performance metrics that may be relevant in the evaluation of clustering performance in terms of classification are accuracy, precision, recall, and F-score.

2.2.3.3 Deep Learning

Deep learning models manage the feature extraction automatically, letting the computer construct complex concepts from simpler concepts [65]. Therefore, it is not necessary to perform feature engineering before training the model, and as a result, the data preparation becomes more straightforward. Deep Learning models can be classified into three types [52]: deep generative models, deep discriminative models, and deep hybrid models.

- Deep generative models aim to learn useful representations of data via unsupervised learning or to learn the joint probability distribution of data and their associated classes.
- Discriminative models learn the conditional probability distribution of classes on the data, in which the label information is available directly or indirectly. CNN and RNN are examples of this type of model.

- Deep hybrid models combine a generative model and a discriminative model where the outcome of the generative model is often used as the input to the discriminative model for classification or regression [66].

In this study we will manage the data as a classification problem using DL.

2.2.3.3.1 Classification

Classification in DL involves categorizing input data into classes based on their features or characteristics. The algorithm classifies the data according to the number of classes the input has, differentiating one class from another.

To perform classification tasks using DL, it is essential to preprocess the data appropriately, choose the right architecture, tune hyperparameters, and train the model on a sufficiently large dataset.

The most important DL architectures (see Figure 2-10) to treat time series data are as follows:

2.2.3.3.2 Neural Networks

- **DNNs:** a simple Deep Neural Network (DNN) model create a mapping between the inputs and class outputs of time-series data doing the feature engineering automatically [67].
- **CNNs:** Convolutional Neural Networks (CNN) is based on convolutions to capture dependencies among input data [68]. This type of architecture is recommended to learn detailed feature representations and patterns from images [69] but the 1D was used because the data is time series.

CNNs typically consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to the input data to extract features. Pooling layers are used to downsample the feature maps, reducing computational complexity. Finally, fully connected layers utilize these features to make predictions. CNN are especially effective for image classification tasks because they can automatically learn hierarchical features from raw pixel values.

- **LSTM:** is the architecture most often recommended to treat time series data because it is the type of Recurrent Neural Network (RNN) used to train the model over lengthy sequences of data. Due to this, it aims to retain the memory from previous time steps to feed the model [70].

Unlike feedforward neural networks, RNN has connections that form a directed cycle, allowing them to capture temporal dependencies in the data.

- **GRU:** this Gated Recurrent Unit (GRU) architecture is a variant of RNN capable of adaptively capturing sequential dependencies. While they have a gated structure, which is similar to that of LSTMs, they are more computationally efficient than LSTMs [71]. LSTM and GRU are the two most used variants of the RNN architecture in movement recognition [72].
- **CNN-LSTM:** Is a hybrid model and reads subsequences of the main sequence as blocks: CNN extracts features from each block, and then allows the LSTM to interpret the features extracted from each block. For this, a Time Distributed wrapper is needed to allow reusing of the CNN model, once per each subsequence, and the CNN output serves as input to the LSTM, which provides the final prediction. In other words, this hybrid model uses CNN layers for feature extraction on input data and LSTMs to support sequence prediction [73].

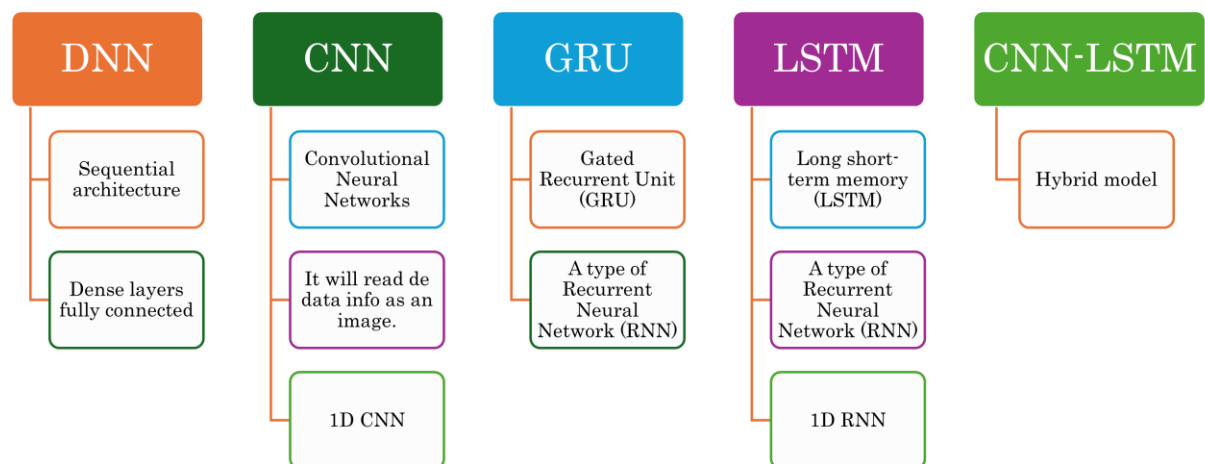


Figure 2-10. DL architectures.

2.2.3.3.3 Performance Metrics

To evaluate classification performance, two metrics were used: accuracy and F1-score. A higher value for accuracy or F1-score indicates better model performance [74]. Also, the confusion matrix and ROC curves were calculated.

- **Accuracy** is the ratio of the number of correct predictions to the total number of input samples [75] and is the conventional evaluation metric when there is no class imbalance [76].
- **The F1-score** combines precision and recall, which are two measures defined in terms of the total number of correctly recognized samples [77].
 - Precision is defined as $\frac{TP}{TP+FP}$
 - Recall corresponds to $\frac{TP}{TP+FN}$, where TP, FP are the number of true and false positives, respectively, and FN corresponds to the number of false negatives [77].
 - Class imbalance is countered by weighting classes according to their sample proportion:

$$F1 = \sum_i 2 * w_i \frac{precision_i * recall_i}{precision_i + recall_i}$$

where i is the class index and $w_i = n_i/N$ is the proportion of samples of class i , with n_i being the number of samples of the i -th class and N being the total number of samples.

- **Confusion Matrix:** is a two-dimensional matrix that displays the true labels in its rows and the predicted labels by a classifier in its columns. This matrix provides a concise overview of the distribution of predictions across all classes [78].
- **Receiver Operating Characteristic Curve (ROC):** is a plot graph of the true positive rate against the false positive rate at different classification threshold setting [79].

2.3 Applications using Wearable IMUs and Artificial Intelligence

Wearable inertial measurement units (IMUs) serve as crucial data collection devices for artificial intelligence (AI) models, as they provide the foundation for AI models to learn from data. This section examines the intersection of these technologies to facilitate human activity recognition (HAR) and balance analysis in individuals with visual impairments.

2.3.1 Human Activity Recognition (HAR)

HAR is used in a large and ever-growing number of applications [80]. HAR ranges from gesture and pattern recognition to motion activity by analyzing the discrete measurements from different types of sensors (e.g., wearable sensors, video surveillance, motion caption system MOCAP). This recognition can be achieved by implementing either Machine Learning (ML) or DL models [81] previously mentioned. With the use of wearable sensors input, DL and ML models have been implemented into several health fields of applications where real-time response is needed. However, DL-based solutions have presented more advantages than ML-based solutions in the engineering feature process, in the recognition of temporal or dynamic features and its high performance [80]. These advantages can benefit applications such as the detection of falls occurrence, an important approach in the ML classification methods [82]. Therefore, DL-based methodologies have been successfully implemented for fall detection and its relation with other human activities and pose recognition, using LSTM [83], [84] CNN, DNN and RNN [85], and other DL-based methods [86]. In DL- and ML-based methods, classification is used to predict a fall from an input sequence of body postures [87]. As the fall is detected the scope increments including other needs to be treated using HAR. Those oriented to sports [88] and rehabilitation [89], [90]; as well as degenerative diseases that involve loss of mobility such as Parkinson and knee osteoarthritis [91], [92], and in assisted living which presents solutions for elderly people and also for people with visual impairments [93].

Most HAR methodologies consist of four stages: data acquisition, data pre-processing, feature extraction, and activity classification [81]. When using wearable sensors as input, related works [94], [95] recommend that segmentation (a procedure used to divide data measurements into smaller fragments, i.e., sliding windows) be performed at the feature extraction stage. Feature extraction is a vital part of the HAR process. It helps to identify lower sets of features (factors) from input sensor data, reduces classification errors, and reduces computational complexity [5].

2.3.2 Balance in Blinds

Firstly, it is evident that vision is a crucial factor in the development of postural reflexes [96]. Blind people present pose problems due to approximately half of the typical sensory input to the brain is lost, which disrupts the normal process of

neurological integration and disintegration and prevents the formation of optimal postural habits. Moreover, although the tactile and auditory senses are developed, these senses are less helpful in maintaining biomechanics.

In addition, to maintain equilibrium, the gait of a blind person deviates from the typical gait pattern. This deviation begins with retraction of the head and includes increased pelvic rotation, excessive backward leaning of the trunk with dorsal kyphosis, compensating forward head posture, abnormal contralateral trunk and arm movements, and flexion contractures. All of these factors contribute to faulty body mechanics. This is achieved by the natural process of compensation in the development of posture.

Over the years, researchers have conducted studies on the topic of posture in VIP. Alghadir et. al, investigated the postural stability if this population taking into account the center of gravity (COG) velocity and comparing with sighted people [97].

Moreover, given the necessity to assess balance in individuals, literature has recommended these principal tests: first, the **Berg Balance Scale (BBS)** is a test used to assess functional balance and evaluate balance ability in the elderly [98]. It lasts 15 to 20 minutes. Second, the **Balance Evaluation Systems Test (BESTest)**, which is a comprehensive balance assessment tool developed to identify the postural control systems underlying poor functional balance. This enables the targeting of treatments to the specific balance deficit. The test can last 35 minutes to administer [99]. It is suitable for use with patients with Parkinson's disease and the elderly [100]. Third, the **mini-BESTest** is an abbreviated version of the BESTest. It is focused on dynamic balance and can be conducted in 10-15 minutes. Most studies conducted on the initial two tests have focused on patients with conditions such as and people with The Mini-Balance Evaluation Systems Test (Mini-BESTest) has been identified as the most comprehensive balance measure for community-dwelling adults and elderly individuals. It can be used to assess balance impairments in several other conditions, mainly Parkinson's disease and stroke [101]. Finally, the **Y Balance Test (Y-Test)** is a dynamic balance assessment typically used in sports medicine [102] It is a commonly utilized tool in both clinical practice and research [103].

Conclusion:

Overall, as previously stated in Section 2.3.1, HAR is employed in applications that utilize data derived from body postures to predict falls. This opens the door for the development of methodologies for rehabilitation in the study of balance for individuals with visual impairments. Because there is no evidence of this balance test administrating to VIP.

Chapter 3. Hypothesis and Objectives

3.1 Hypothesis

There are technologies that are used to detect and record the movement of the human body. One of the most well-known is the MOCAP system, which is based on cameras, and the other is the Inertial Measurement Unit (IMU). IMUs are known to be less expensive and less invasive devices than MOCAP systems. Starting from this premise, we propose that the use of low-cost inertial sensors as a basis for the construction of human movement registration systems for the recognition of human activities is possible and reliable, at the level of systems based on image recognition. Therefore, they are a suitable alternative to these methods for numerous application situations. In this sense, we propose as an initial application, as a case study, to test this hypothesis, the study of balance analysis methods in blind people. An extension of this study to non-blind people is currently being carried out, but as it is not yet completed it is outside the context of this doctoral thesis.

3.2 General Objective

The main objective of this thesis is developing methodologies for testing the information's quality of low-cost IMU's, incorporating the use of Artificial Intelligence algorithms to recognize human activities, discarding systems that include cameras such as: MOCAP. As a result, the solution will be less invasive and more accessible.

3.2.1 Specific Objectives

To meet the main objective proposed is necessary to review mobility orientation's topics to recognize the needs for developing new solutions as well as following these stages:

- Use of Unity to create a mobile orientation app in an indoor space.
- Test and compare devices for capturing body movement (inertial sensors and Motion Capture systems).
- Select appropriate AI algorithms for human activities recognition using time series data.

- Explore supervised learning techniques.
 - Deep Learning.
- Explore unsupervised learning techniques.
 - Machine Learning - Clustering
- Implement a balance test named mini-BESTest and adapt it to visual-impaired people.
- Launch OpenSense RT, a prototype developed by Stanford University's laboratory as data collection device.
- Collect data from people's movements when doing balance test mentioned above, since there is currently no database that includes blind people data.
- Evaluate people's balance by a physiotherapist.
- See if using AI, we are able to classify a person's balance according to the score given by the physiotherapist.
- Evaluate characteristics: how many inertial sensors are necessary to extract valuable information to help in prediction using AI algorithms.

Chapter 4. Methodology

To have a big picture of the scope of this thesis we must start mentioning the dispositive tested for data acquisition, its functions, and differences; as well as an applied case where one of them was implemented.

4.1 Initial Methodologies: Developed Assessment of Orientation and Mobility.

Firstly, the orientation and mobility of individuals with disabilities is a crucial aspect when they are learning how to be freer or autonomous. This is also the case for individuals with new disabilities, whether they require rehabilitation or not.

4.1.1 Indoor Guide System with Unity

Along the last years people are creating technology aids for orientation and mobility in blinds. First, the use of mobile applications to guide them into a space that they have not been before was created in the lab. This methodology used Unity software as a platform to create a video game where the user is an avatar through all the indoor space. This kind of application basically implements GPS, Bluetooth, to locate in the room.

On the basis of the above **a mobile indoor guide system** was built to give a track guide for where the avatar (the user) must pass to reach the interest point. It was created with Unity due to the use of AR and VR. Additionally, the mobile app was created for iOS users due to most VIP using iPhone instead on Android.

The solution is divided into three parts:

- A client side: the mobile phone represents the device that will provide input data and signaling. This will be the iPhone mobile phone. Additionally, a recognition indicates the native software recognition connection between the device and the ARKit SDK. Furthermore, an ARKit processing element is present, which is native to Apple software and controls the AR surface recognition processing in order to work properly with this information.
- Middleware layer: is present on both sides. Management functions as a controller, orchestrating the flow of data between the client and server. It is responsible for organizing and processing the information required by the

system. In the context of this project, it is Unity 3, a customized API developed in-house.

- Placenote SDK: includes a Metadata Storage, which holds all the technical information needed to differentiate between the stored maps. Additionally, it contains a Map Storage, which allows for the identification of the spatial position within a specific map. Furthermore, the SDK incorporates a Waypoints Storage, which stores the relevant data required to place the different waypoints on the map that mark a specific pathway.

The components operate in sequence. A blind person enters a new room that they have not previously visited. This room has been previously virtualized, and maps have been created to generate waypoints to support guidance. When the application starts, we check that the person is ready with bone headphones to follow 3D simulations. Then we place a target, and the person will navigate to it. The instructions that are given through the application will be heard through the headphones. Finally, we will demonstrate the waypoint path. In this case, the visual and auditory information is provided by the API, which establishes a connection between the user and the device. The user can then navigate through the environment, which is represented by a 3D model. The user can also interact with the environment by issuing commands through the application.

4.1.2 AI for Calculating Cognitive Map Quality from Scene's Images learnt by VIP to be Orientated - Photo Vector Extraction using Deep Learning Techniques for Cognitive Map Index Calculation.

The doctoral thesis of Antonio Cobo defined a quality index to quantify the similarity between two different distributions of the same scenario in a single numerical value. This index, named SUQI (Spatial Understanding Quality Index), aimed to create a method without the limitations of currently available cognitive map evaluation models. The index is defined as the Mahalanobis distance Eq. 1:

$$d(\vec{x} - \vec{y}) = \sqrt{(\vec{x} - \vec{y})^T \mathbf{S}^{-1} (\vec{x} - \vec{y})}$$

between a given spatial product and the corresponding original scene. The smaller the resulting Mahalanobis distance between two scenes, the higher the quality of the cognitive map.

The Mahalanobis distance between two spatial products, represented by vectors $\vec{x}$ and $\vec{y}$, respectively, is given by the square root of the following expression: The calculation of the Mahalanobis distance requires consideration of the reference scene, which is defined by values of (0, 0, 0, 0, 0) for the indices that define its vector.

A total of 19 participants with total blindness were recruited for this study. They were then asked to virtually walk through three different scenarios: a bedroom, a bar and an office. Each scenario contained a number of structures, including windows, doors, columns, and different objects. There were six of each in each scenario. The tour was conducted via an application on a mobile phone, which positioned a character in the virtual environment and allowed the user to navigate through it by means of touchscreen interactions and device-internal gyroscope readings. Participants were encouraged to explore each of the target scenes until they felt they had a comprehensive understanding of the layout.

Through this project we studied the use of virtual spaces designed for blind people to explore unfamiliar areas before physically walking through them.

To replicate the results of the previous scans, we took photos of the same scene to create our database. Second, the images were processed manually. It was calculated 3 of the 4 vectors necessary to get SUQI through Mahalanobis measure Third, the vectors which work with are Identification, Absolute position, and Relative position. Additionally, the vector who is involved with the structure is not taken into consideration because we do not have a mock-up to compare each other. Once the database was complete, we trained deep learning (DL) algorithms to predict the vector values automatically from the images of the models. To assess the quality of the cognitive maps, we used two variables: the CMQ index value and the participants' fluency in recalling their content.

In conclusion, convolutional neural networks (CNNs) proved to be effective in extracting features from bar scene images. A shift from regression to classification was observed, highlighting the complementary nature of both approaches. Regression requires a large amount of data for accurate prediction, while classification requires a balanced distribution of classes. The proposed model achieved an error of 0.062 for 500 photos, improving to 0.031 for 800 photos. However, performance varied across vectors, with errors of 0.073 and 0.121 for the identification and relative position vectors, respectively. Further development and

larger sample sizes are needed for implementation, but the results are promising and highlight the importance of additional samples for improved accuracy.

4.1.3 Dispositive to Measure People Displacement using the Long Cane.

Our research involved exploring the information provided by IMU sensors placed on the cane, including sweeping coverage and gait analysis. These data are currently visually analyzed during rehabilitation.

Data acquisition: The system was tested with ten blindfolded volunteers in laboratory conditions. The volunteers were instructed to use the cane in constant contact, two-point and three-point touch techniques for blind individuals, as described in the O&M book.

The quantification system is reliable for measuring the following variables:

- Grip rotation
- Safety zone
- Sweeping amplitude
- Hand position

The orientation angles were used to measure these variables, resulting in an accuracy of approximately 97.62%. However, a new method or an improvement of hardware must be developed to improve gait parameters' measurements, since the step length measurement presented a mean accuracy of 94.62%.

The system requires further development to be used as an aid in the rehabilitation process of the VIP. The device is a straightforward and cost-effective technological aid with the potential to enhance the current practice of O&M.

4.1.4 Real-time Indoor Human Activity Positioning using IMU Data and DL Algorithms.

The goal of the project is to predict the position of an individual in an indoor environment using a free database and DL algorithms.

The database is composed of acceleration, orientation, gyroscope, and magnitude data in 3D (x, y, and z). Each data point is associated with an identifier, which

itself is associated with a 2D position (x and y) coordinates. We created a mobile application to replicate the database in a room and acquire more data.

Once we had the data, we applied DL algorithm to predict the subject's position in x and y coordinates. In this case is a regression problem and each data from the IMU's of the phone (acceleration, gyroscope, and magnetometer) was labelled with its corresponding position in x and y.

We compare three DL models: a Multi-Layer Perceptron (MLP), a Long Short-Term Memory (LSTM), and a hybrid model made of a combination of a Convolutional Neural Network with a Long Short-Term Memory Network (CNN - LSTM). Once we obtained the train model, we converted it to TensorFlow lite to add it in the real-time application that was made for Android. However, more data must be collected to expand the database and retrain the algorithms to achieve a higher level of accuracy.

Conclusion: The previous methodologies tested until this phase included positioning and guiding solutions, as well as techniques to improve the rehabilitation process. Additionally, we incorporated AI algorithms to treat images and wearables data. Hence, now we can move to the next phase, which involves comparing two acquisition devices and using AI for HAR to study human daily activities.

4.2 Comparison of IMU's and MOCAP Systems for Recognizing Human Activities using Deep Learning and Study of Sliding Window's Variation.

This methodology was tested in our internship in Instituto Superior Tecnico de Lisboa and INESC-ID: studied the importance of sliding window sizes as a segmentation tool in HAR and also compared four different Deep Neural Networks to make the classification taking as input the data from IMU and MOCAP. In other words, the novelty of this research is the combination of both: automatic feature extraction process performed by DL architectures and sliding window creation as pre-processing segmentation data in order to find an optimal window size that provides the most accurate activity classification.

4.2.1 Data Acquisition

The performance of the different networks was tested by evaluating the linear acceleration data of three daily movements: *walking*, *sit-to-stand*, and *squatting*. The experimental acquisitions were done in the Lisbon Biomechanics Laboratory at Instituto Superior Técnico using two motion capture systems: a low-cost inertial measurement system based on two MetaMotionR sensors (MBIENTLAB INC, San Francisco, CA., USA) and a high-end optoelectronic system composed of 14 infrared ProReflex 1000 cameras (Qualisys©, Göteborg, Sweden). The study was approved by the ethics committee of Instituto Superior Técnico in January 2020 (Ref. nr. 1/2020 (CE-IST)). All volunteers expressed their agreement to participate by signing an informed consent after a detailed explanation of the study objectives and experimental protocol. The inertial measurement acquisition protocol consisted in the use of two wearable sensors placed on the left wrist and left ankle. Simultaneously, a 2D full body protocol, composed of 24 retro-reflective makers placed on anatomical landmarks as suggested by ISB [104], [105], was implemented to acquire the volunteer's motion with the optoelectronic system. Two more markers were placed over the IMUs to directly compare the neural network predictions from the two systems (see Figure 4-1).



Figure 4-1. Representation of the experimental protocol: a) Ankle sensor; b) Wrist Sensor.

Ten healthy volunteers (M:6, F:4; Age: 30.0 ± 6.3 years; Height: 1.70 ± 0.11 m.; Weight: 69.7 ± 15.3 kg.) were selected based on the inclusion/exclusion criteria defined in the ethics committee proposal. The acquisitions with the two systems were done simultaneously using a sampling frequency of 100 Hz. The MOCAP data was processed using the Qualisys Tracking Manager software and the IMU data with the MetaBase App. For the gait analysis, volunteers were instructed to walk continuously for 60 seconds; this procedure was repeated three times. For the

remaining movements, volunteers performed three series of ten repetitions each. All the trials were performed after a period of adaptation to the laboratory environment.

4.2.2 Data Pre-processing

The experimental dataset consisted of 304,135 samples for the IMU system and 315,334 for MOCAP and included 3-axis acceleration for each sensor and marker placed in the left ankle (lateral malleolus) and left wrist (posterior region), and a label indicating the performed activity. The final dataset has six entries or features ($x_1, y_1, z_1, x_2, y_2, z_2$). The label contained the three classes of expected activity (walking, sit-to-stand, squatting).

As shown in Figure 4-2. From top to bottom are the signals that correspond to accelerations in x, y, and z for each IMU sensor. The first three belong to the sensor that was placed in the arm and the second to the ankle, respectively. Due to sit-to-stand being similar movements the acceleration in y_2 which is notorious in green color for walking is not oscillating in the two last activities because to do those activities the participant stayed almost static.

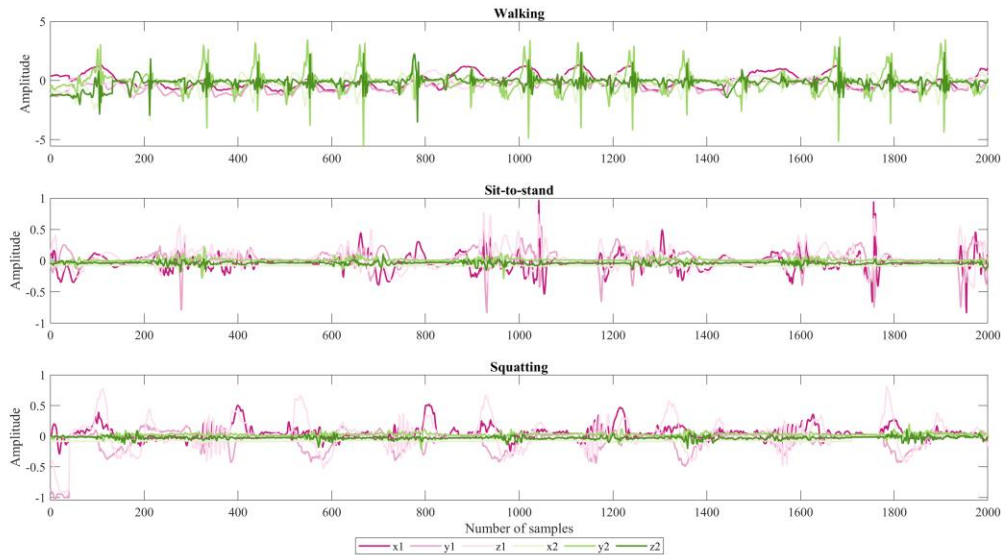


Figure 4-2. Representative set of IMU signals from participant 1.

Considering that the data to evaluate the Deep Learning Models needs to be split in training and testing, two databases per system were created: one for training with the raw data of eight volunteers and the other, with two different volunteers,

for making the predictions. Hence, the IMU dataset comprised a total of 281,161 training samples and 99,108 validation samples; and the MOCAP dataset included 247,804 and 67,530 samples for training and validation respectively.

4.2.3 Sliding Windows Creation

This study implemented fixed overlapped sliding windows by dividing all samples into a window of size n . A feature is the input of the sequence, in this case: $x_1, y_1, z_1, x_2, y_2, z_2$, and corresponds to one observation as a time step. The dataset was acquired with a sample rate of 100 Hz, and the first implemented window had a duration of 1 second, consisting of 100 frames. The approach involves reducing the window size, (25, 20, 15, 10, 5 frames), resulting in a decrease in time length from (0.25, 0.20, 0.15, 0.10, 0.05 seconds), respectively, to determine the optimal window parameters.

For instance, to create a sliding window of size 5, the total number of samples is divided by the timesteps, which include all the columns involved in the observation, resulting in an input shape of (281156, 5, 6). As shown in Table 4-1, as the window size increases, the total of samples decreases because the size of the window is subtracted from the total. In other words, a greater number of samples per window size is observed when using a larger window that slides from the beginning to the end of the time series.

Table 4-1. IMU and MOCAP window sizes' distribution for 8 people for training the model.

System	Total number of samples (8 subjects)	5	10	15	20	25
IMU	281161	(281156, 5, 6)	(281151, 10, 6)	(281146, 15, 6)	(281141, 20, 6)	(281136, 25, 6)
MOCAP	247804	(247799, 5, 6)	(247794, 10, 6)	(247789, 15, 6)	(247784, 20, 6)	(247779, 25, 6)

⁴⁻¹ Window sizes for IMU and MOCAP.

Therefore, in this study, two sets of different windows have been created: one of shorter lengths (5, 10, 15, 20, and 25 frames), and the other of longer lengths (50, 75, 100, and 200 frames), in order to compare the performance metrics (accuracy and F1-score) that are achieved for each tested architecture of Deep Learning, thus

allowing us to find the window size that would be optimal to reduce the cost of processing.

4.2.4 Artificial Intelligence Models

Although a simple DNN manages time-series data without using sliding windows, this study includes the creation of sliding windows to give an equal input setup to each AI architecture. CNN and LSTM models require an additional step to convert the problem into a supervised learning problem, as the input data must have a three-dimensional structure instead of a two-dimensional format that raw inertial sensors and motion capture system data have [106].

The parameters for each architecture planned from simple to robust were set as shown in Table 4-2.

A schematic of the four architectures is presented in Figure 4-3. First, a simple DNN was implemented using fully connected layers. Three dense layers of 32 neurons were set, a flatten layer and a SoftMax were used to get the output (see Figure 4-3-1). Second, a one-dimensional Convolutional Neural Network (1D-CNN) was used within a filter and kernel of size three; a dropout of 0.5 to minimize overfitting, a max-pooling layer of size two, a flatten and a dense layer of 8 neurons, and a SoftMax (see Figure 4-3-2).

Table 4-2. Parameters of each Deep Learning Architecture.

Parameters	DNN	CNN	LSTM	CNN-LSTM
Layers with Neurons	3 Dense (32 neurons), Flatten, SoftMax	1D-Conv (32 neurons, filter=3, kernel=3), MaxPooling (size=2), Flatten, Dense (8 neurons), SoftMax	LSTM (100 neurons), Flatten, Dense (100 neurons), SoftMax	2 1D-Conv (64 neurons, filter=3, kernel=3), MaxPooling (size=2), Flatten, LSTM (100 neurons), Flatten, Dense (100 neurons), SoftMax
Dropout rate	0	0.5	0.5	0.5
Activation function	ReLU	ReLU	ReLU	ReLU
Optimizer	Adam	Adam	Adam	Adam
Loss function	Sparse categorical crossentropy	Sparse categorical crossentropy	Sparse categorical crossentropy	Sparse categorical crossentropy
Batch size	64	32	64	64

Epochs	100	100	100	100
⁴⁻² Software: Python, Tensor Flow, Google Colab.				

Third, an LSTM architecture was used that comprises 100 neurons, a dropout of 0.5, a dense layer of 100 neurons, the SoftMax to obtain the output as shown in Figure 4-3-3.

Finally, a hybrid model named CNN-LSTM was chosen as the last architecture. As shown in Figure 4-3-4, the hybrid model comprises a 1D-CNN with 5 layers and an LSTM with 4 layers.

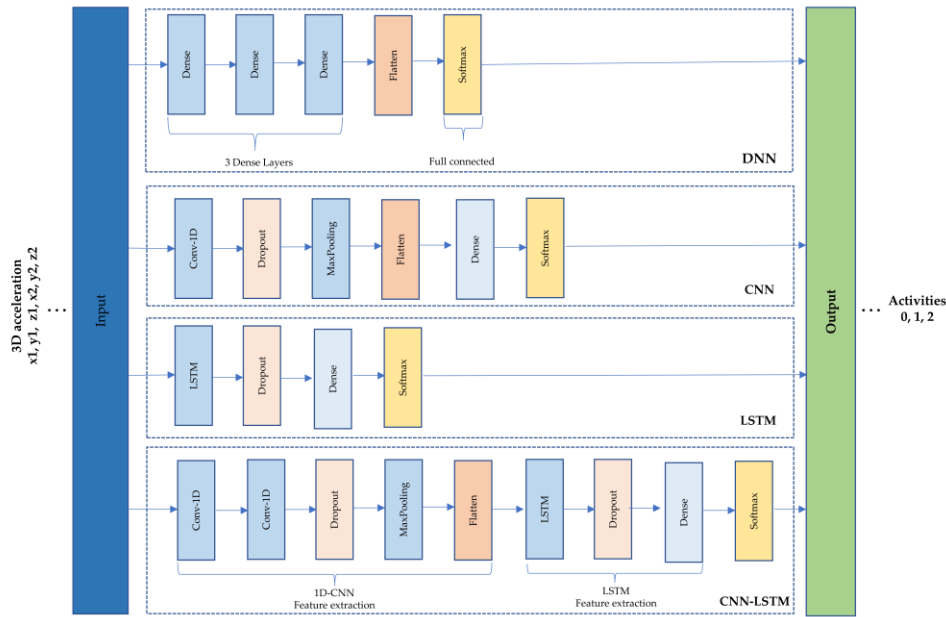


Figure 4-3. (1) Deep Neural Network architecture (2) Convolutional Neural Network architecture. (3) Long Short-Term Memory architecture. (4) Hybrid model (CNN-LSTM) architecture.

4.2.5 Performance Metrics and Evaluation

The performance is measured using the loss function sparse categorical cross-entropy. This function is used when there are two or more label classes which are integers. In our case, there are three labels or classes provided (0, 1, 2) for walking, sit-to-stand, and squatting. Also, as the activation function rectified linear unit activation (ReLU) was chosen. Regarding optimizers, the Adam algorithm was used which is a stochastic gradient descent method that is based on adaptive estimation of first-order and second-order moments.

To evaluate the classification performance of each deep learning model two metrics were chosen: accuracy and the F1-score.

Another parameter must be included because this study presents class imbalance for MOCAP (refer to Figure 4-4). Therefore, the F1-score is considered, which accounts for the class imbalance by weighting the classes according to their sample proportion. Due to constraints with the volume of acquisition of the MOCAP system, the dataset for this system is not fully balanced. In particular, the number of frames for the walking movement is 35% less than the big one as shown in Figure 4-4. For this, the F1-score is considered which counts the class imbalance by weighting the classes according to their sample proportion.

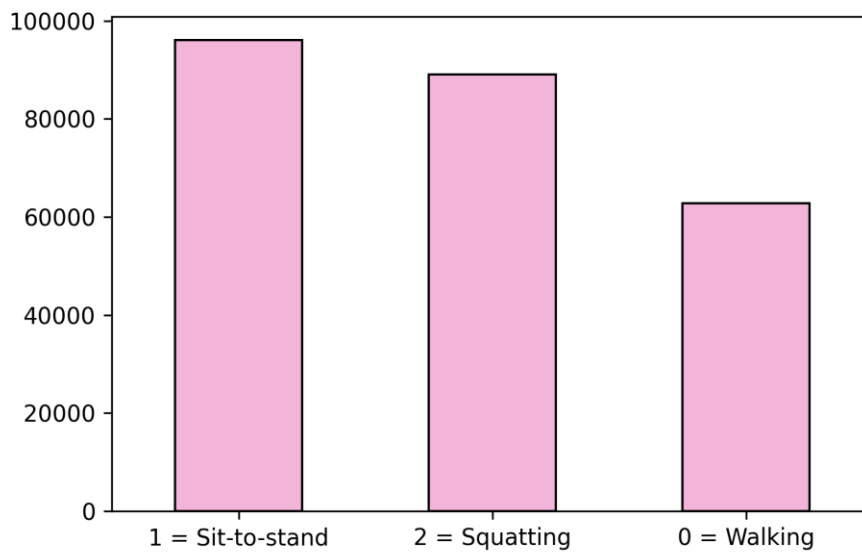


Figure 4-4. Class 0 is not equally balanced.

The results can be found in Section 5.1.

4.3 Applied Case – Balance in Blinds using DL

During the last year of this thesis, we proposed an applied case to study the balance in blinds. Blinds are people who presents pose problems and posture are very related with balance. The vestibular system is very important and plays a fundamental role in a person's balance. This system is fully developed in sighted people, they have the sense of sight and hearing. However, we want to see if we are able to find differences in the balance of blind versus sighted people, as the vestibular system is compromised, they are in the absence of vision.

For carry out the applied case, different steps were taken. First, we did a search to select which IMU's we were going to use to acquire the data. Our findings show a prototype named OpenSense RT for recording information. Second, we selected the mini-BESTest as balance tests to assess balance's performance. Third, we selected the AI algorithms to test the data. Finally, we obtained the results following different AI methodologies. Those results are in Section 5.2.

4.3.1 Open Sense RT Adaptation

OpenSense RT [91] is a prototype developed at Stanford University. It is based on a Raspberry Pi that controls IMU's sensors to model people skeletons when moving. This prototype has the characteristics of modeling the body kinematics in real time, but you can choose whether real time or only raw sensor's parameters. Figure 4-5. Illustrates the body sensor's placement in OpenSense RT.



Figure 4-5. OpenSense RT diagram. Credits:⁵

An adaptation was made for our application. First, 12 IMU's ISM330DHC were selected to register the information from the body's parts: pelvis, left and right feet, left and right shank, left and right hand, left and right arm, torso, C5 and head. Second, the decision was made to record the raw data only in order to use it further

⁵ P. Slade, A. Habib, J. L. Hicks, and S. L. Delp, "An open-source and wearable system for measuring 3D human motion in real-time," *IEEE Trans Biomed Eng*, vol. XX, no. Xx, pp. 1–10, 2021, doi: 10.1109/TBME.2021.3103201

with AI models. Consequently, the parameters were selected offline instead of online. The kinematics were not processed because the focus was on offline work. Figure 4-6 illustrates the customized IMU placement in the body.

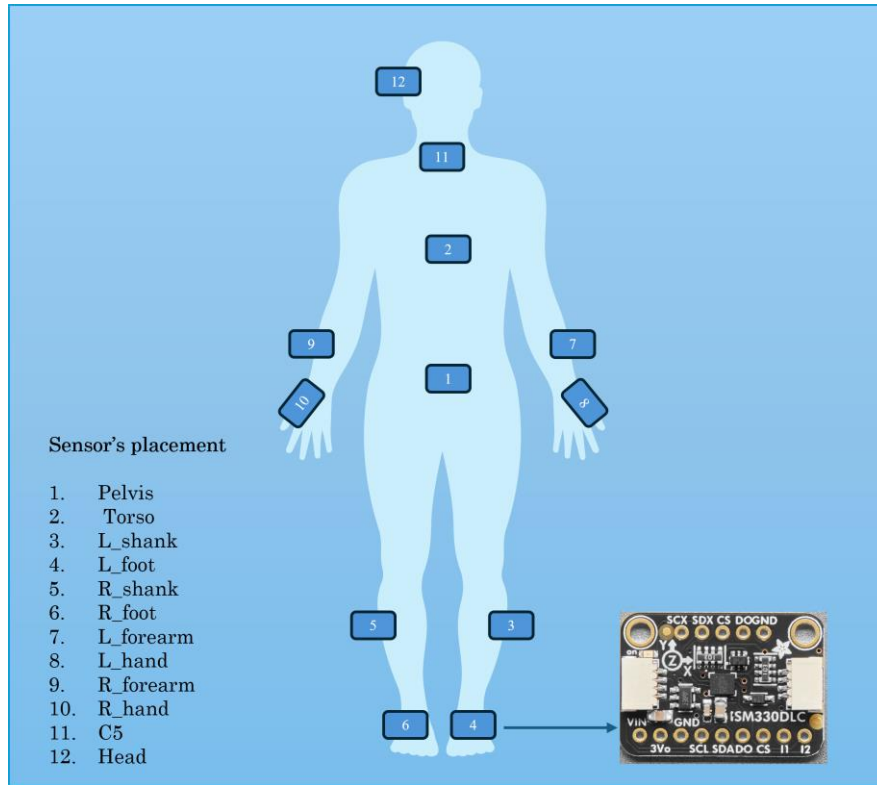


Figure 4-6. Adaptation for Applied Case – Sensor's Placement in the Body

4.3.1.1 Data Acquisition

The study was conducted at two locations: Centro de Tecnología Biomédica (CTB) and Organización Nacional de Ciegos de España (ONCE). Fifteen healthy sighted individuals (M:6, F:9; Age: 25.87 ± 5.49 years; Height: 1.65 ± 0.07 m.; Weight: 63.53 ± 8.10 kg.), participated at the first location; and fourteen healthy blind individuals (M:6, F:8; Age: 40.14 ± 10.56 years; Height: 1.65 ± 0.09 m.; Weight: 69.86 ± 10.22 kg.), participated at the second location. A total of twenty nine healthy volunteers (M:12, F:17; Age: 32.76 ± 10.93 years; Height: 1.65 ± 0.08 m.; Weight: 66.59 ± 9.57 kg.) participated in the study.

Although the statistical power has not been calculated, and to have it would require a considerable number of participants, the availability of participants is much lower. Therefore, we proceeded with the 14 VIP participants who were available. Furthermore, the number of participants is comparable to those used in

current studies, which typically include 9, 11 and 12 participants [107], [108], [109].

Additionally, data were collected at a frequency of 50Hz, and triaxial measurements of acceleration and gyroscope were obtained as presented in Table 4-3. The mini-BESTest was completed by each participant in approximately one hour. And the test was recorded on video for further evaluation by experts.

Table 4-3 Data acquisition parameters

Participants		Sampling rate (Hz)	DOF IMU	Data type
Sighted	Blinds			
15	14	50	6	Acceleration + Gyroscope

Furthermore, the ethics committee of Universidad Politécnica de Madrid (UPM) (ADPCEPCDVY-JJSO-DATOS-20230329), previously approved all information related to the informed consent, study objectives, and experimental protocol, as stated in Appendix A.

4.3.2 Mini-BESTest Blind-Adaptation

As stated in the State of the Art, the mini-BEST test was primarily used to treat individuals with Parkinson's disease. However, as our goal was to treat visually impaired individuals. For this, two experts recommended adapting the test. Figure 4-7 displays all the activities included in the test.

The adapted test has mainly reduced the duration of each exercise to allow blind participants to complete them. For instance, in Test 3, the time has been reduced from 15 seconds to 10 seconds. Please refer to Appendix B. to access the adapted test which is in Spanish.

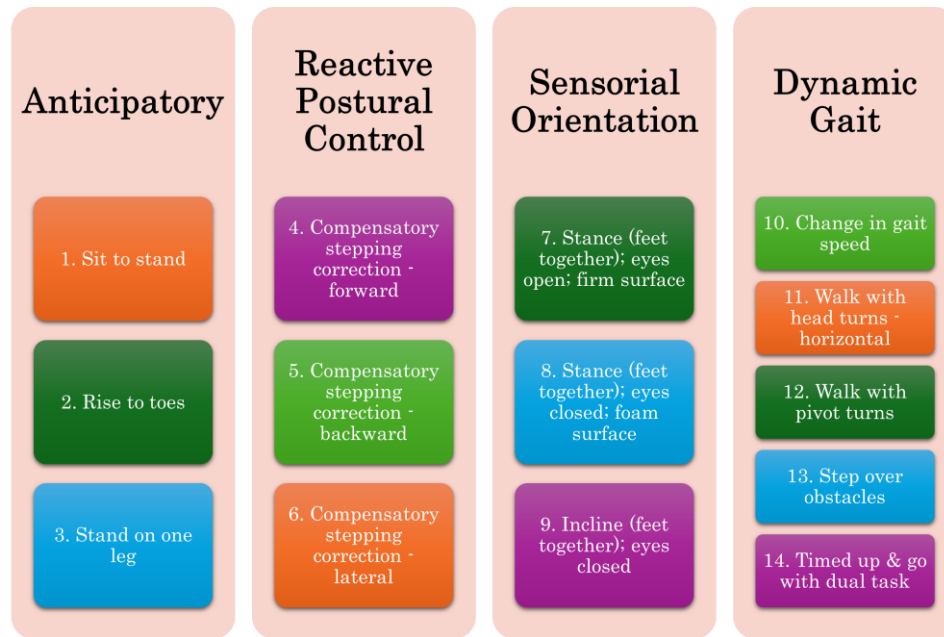


Figure 4-7. Mini-BESTest Areas of Study and Activities.

4.3.3 Mini-BESTest Evaluation

The mini-BESTest Spanish adaptation evaluates balance by considering each exercise separately. A ranking of 0, 1, and 2 corresponds to bad, mild, and good balance, respectively. Some exercises require both left and right-sided execution. Therefore, the final evaluation takes into account the worst-case scenario. For example, if the left-sided execution was worse than the right-sided, the final score for that activity must be left-sided. The rules for evaluating the mini-BESTest are detailed in Section 5.2.1

4.3.3.1 Cohen's Kappa Coefficient

Cohen's κ coefficient determines whether the degree of agreement between two raters is higher than would be expected by chance[110].

It assumes that:

- The subjects being rated are independent of each other.
- The categories of ratings are independent, mutually exclusive, and collectively exhaustive.
- Two raters operate independently. In addition to the three statistical assumptions, Cohen's κ further assumes that the "correctness" of ratings

cannot be determined in a typical situation, and raters are deemed equally competent to make the judgment on a prior ground [111].

The formula for computing Cohen's κ is expressed in Eq. 2:

$$\kappa = \frac{P_0 - P_c}{1 - P_c}$$

where P_0 = the proportion of units in which the judges agreed, and

P_c = the proportion of units for which agreement is expected by chance.

The Cohen's Kappa coefficient was calculated to know the degree of agreement between the two evaluators who scored the mini-BESTest.

4.3.4 Data Pre-processing

This thesis primarily utilizes data cleaning and normalization techniques. For normalization, the Standard Scaler function from the scikit-learn library was employed. This function removes the mean and scales the data to unit variance. In other words, it standardizes each column's values to have a mean of 0 and a standard deviation of 1. Additionally, the files were processed by adding the columns such as ID, timestamp and label to each file. Figure 4-8 displays the file configuration.



Figure 4-8. Files Set-up.

4.3.5 Correlation

This thesis employs Pearson's correlation coefficient, a method suitable for linear relationships between variables that does not consider outliers. The implementation of this method in Python is achieved through the scikit-learn library and the `corr()` function. The correlation is calculated by examining the evaluation table for mini-BESTest displayed in Section 5.2.2. This table comprises fourteen activities, four parts, and a total score, which collectively constitute a well-balanced test scale. In addition, we considered qualitative and quantitative

values corresponding to important participant information, such as age, height, weight, gender, and whether they practice sports.

4.3.6 AI Methodology

The applied case study was divided into two methodologies. The first methodology employed machine learning to explore population characteristics, while the second methodology used deep learning to analyze IMU data and the test’s punctuation. The AI methodology is illustrated in Figure 4-9.

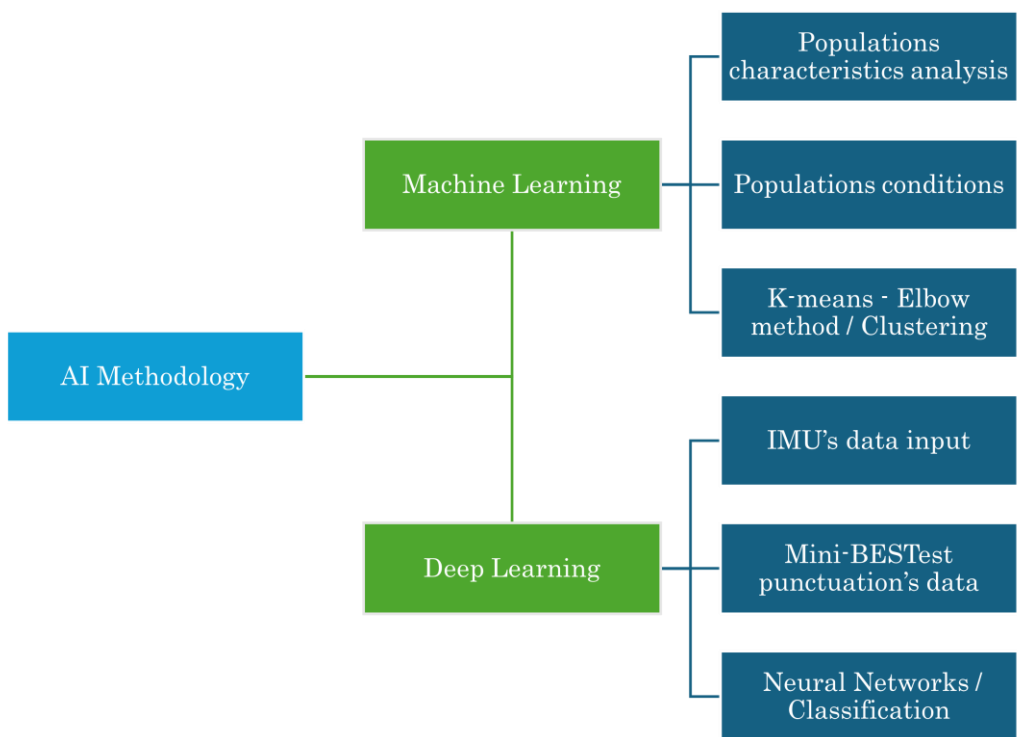


Figure 4-9. AI Methodology.

4.3.7 Machine Learning

In terms of machine learning techniques, this thesis uses a feature selection algorithm RFE using linear regression to select the most relevant features, and clustering specifically K-Means to differentiate groups from the dataset as shown in Table 4-4.

Table 4-4. Machine learning architectures.

Algorithm	Parameters
RFE	n_features_to_select = k from 1 to 14
K-Means	n_clusters = k (Elbows method)

4.3.7.1 Deep Learning

In this case, we tested four architectures based on our previous work on HAR and also considered adding a GRU model. Table 4-5 shows the setup of the models.

Once the model architecture is selected, we must follow a series of steps to obtain the final prediction, which in this case is the classification that corresponds to the punctuation of a particular activity in the mini-BESTest. The AI workflow for obtaining the prediction includes training the model, tuning the hyperparameters, model validation, and model testing.

Table 4-5. Deep Learning Architectures.

Parameters	CNN	LSTM	GRU	CNN-LSTM option 1
Layers with Neurons	1D-Conv (32 neurons, filter=3 kernel=0), MaxPooling (size=2), Flatten, Dense (64 neurons), SoftMax	LSTM (100 neurons), Dense (100 neurons), SoftMax	GRU (64 units), GRU (32 units), Dense (64 neurons), SoftMax	1D-Conv (filter=16 kernel=5), 2 1D-Conv (filter=64 kernel=3), MaxPooling (size=2), Flatten, LSTM (20 neurons), Flatten, Dense (20 neurons), SoftMax
Dropout rate	-	0.5	-	0.5
Activation function	ReLU	ReLU	ReLU	ReLU
Optimizer	Adam	Adam	Adam	Adam
Loss function	Categorical crossentropy	Categorical crossentropy	Categorical crossentropy	Categorical crossentropy
Learning rate	0.0001	0.0001	0.0001	0.0001
Batch size	32,64	32,64	32,64	32,64
Epochs	20, 50, 100	20, 50, 100	20, 50, 100	20, 50, 100

⁴⁻⁵ Software: Python, Tensor Flow, Visual Studio Code

First, model training is the process by which a model learns from labeled data and identifies patterns that relate to the label data. It is also important to tune the model by varying hyperparameters such as epochs, batch size and learning rate to optimize the model's performance. To validate the model, it should be evaluated using a validation dataset that is different from the one used for training. This allows for analysis of how well the model generalizes and whether further adjustments are necessary.

Second, model testing involves observing the model's behavior when data that was not used for training or validation is excluded during training. This allows us to evaluate the model's performance with real-world data.

Additionally, this thesis employs Nested Cross Validation, a technique for evaluating and tuning AI models to ensure their performance on unseen data. Figure 4-10 illustrates how Nested Cross Validation implements k-fold cross-validation in an outer loop to split the data into training and test sets. Within this outer loop, another inner loop of Leave-One-Out Cross-Validation (LOOV) is implemented to tune the model's hyperparameters (epochs, learning rate and batch size) on the training set. The outer loop evaluates the performance of the tuned model on the test set. This approach provides a more comprehensive evaluation of the model's performance and helps prevent overfitting of hyperparameters.

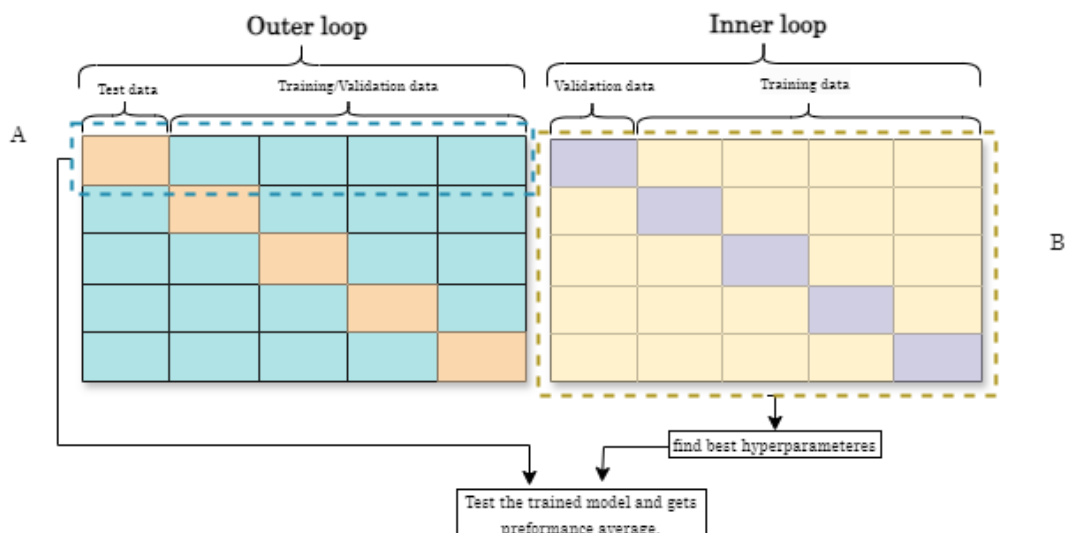


Figure 4-10. Nested Cross-Validation Diagram.

4.3.7.1.1 Input Data Methodologies

Mainly, the evaluator should consider the worst-case scenario if the activity were executed by both legs. This thesis presents two methodologies for using the Test 3 dataset as input data for the DL models. Figure 4-11 shows the first option, which considers the final punctuation obtained by the worst-case scenario, including the two files per participant corresponding to both legs. If the files do not have the same punctuation, replace the file with the higher punctuation with the one that has the lower punctuation. If both files have the same punctuation, keep both of them. Additionally, as a second option, the final label for each leg corresponds to the expert's evaluation of each leg separately.

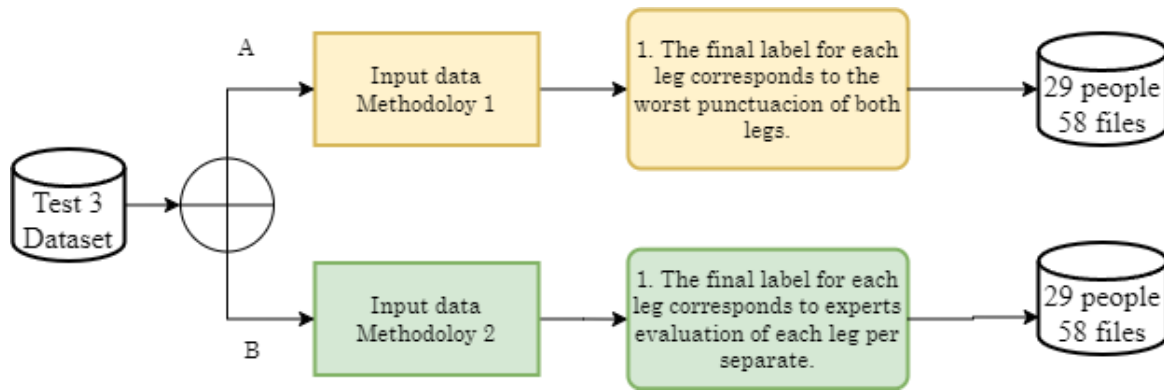


Figure 4-11. Input Data Methodologies.

4.3.7.1.1.1 Input Data Methodology 1

As an initial approach, we used the IMU data from both legs as input and the final evaluation of Test 3 as output. We created a code to add the information of each participant's leg and labeled the output with the final punctuation of Test 3 (the worst when performing the activity with both legs. Additionally, we will test the models for data inputs as presented in Table 4-6. For instance, when examining acceleration, the data input comprises 36 features, whereas acceleration + gyroscope comprises 72, and quaternions comprise 48, respectively.

Table 4-6. Input Data Types.

Input data	Number of Sensors	Number of variables per sensor	Features
Acceleration	12	3	36
Acc + gyro	12	6	72
Quaternions	12	4	48

4.3.7.1.1.2 Input Data Methodology 2

The second scenario to evaluate is to analyze the information and the scores of each leg separately, meaning that the evaluation made for each leg before the final one remains unchanged.

Additionally, we considered two options as input data to test the model's prediction accuracy: raw acceleration and quaternions. This decision was made to analyze the model's performance with less feature-rich data and to compare the results between raw acceleration and quaternions. Because quaternions involve more data processing.

Finally, four DL models were tested: CNN, LSTM, GRU, and two variations of the hybrid model - CNN-LSTM (option 1 and 2, with 1 being the complex and 2 being the light one). The models' schematic for the CNN-LSTM option 2 is shown in Figure 4-12.

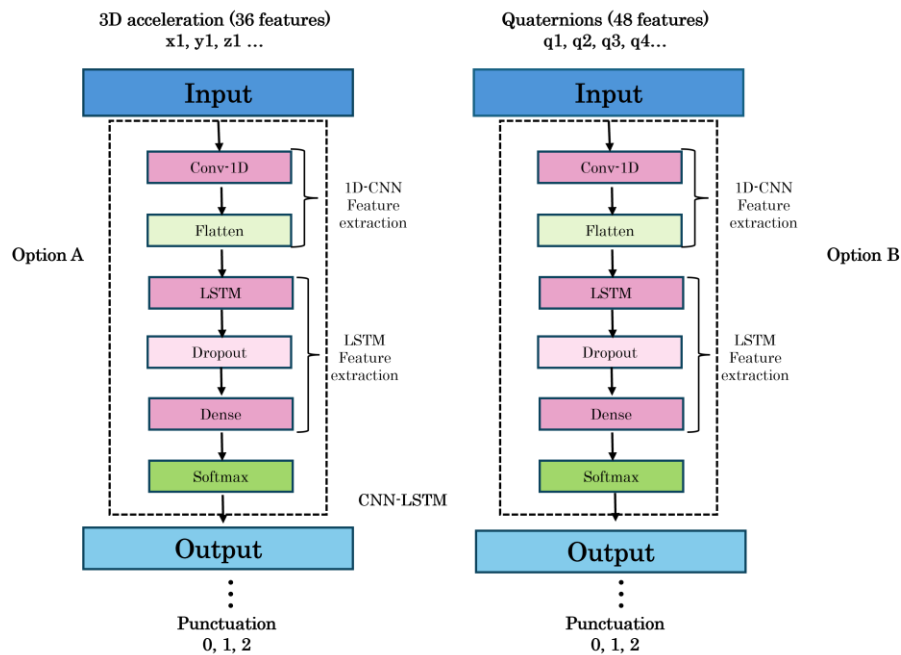


Figure 4-12. CNN-LSTM Model Option 2.

4.3.7.1.2 Determination of the Optimal Number of IMUs on the Body

To determine the minimum number of sensors required for accurate classification in Test 3, we decided to use a criterion coming from an expert. We excluded four, five, and six sensors based on the body parts that were less relevant to the movement while *standing on one leg (Test 3)*. These options are explained below:

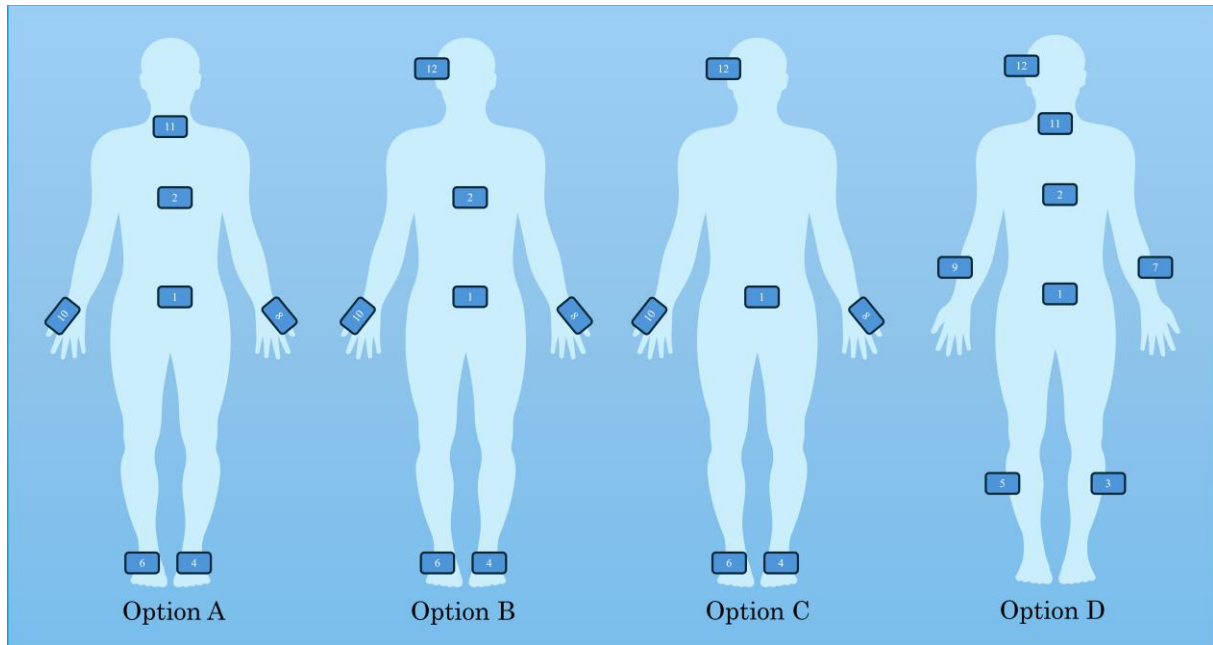


Figure 4-13. Sensor's Placement Options.

4.3.7.1.2.1 Option A

In this option we deleted the left and right shank, left and right forearm, and head, a total of five sensors. We considered the remaining *seven sensors*, including the pelvis, left and right hand, left and right feet, torso, and C5.

4.3.7.1.2.2 Option B

In this option, the left and right shanks, left and right forearms, and C5 were deleted, resulting in the removal of five sensors. The remaining *seven sensors*, including the pelvis, left and right hands, left and right feet, torso, and head, were considered.

4.3.7.1.2.3 Option C

In this option we deleted the left and right shank, left and right forearm, C5, and torso, a total of six sensors. We considered the remaining *six sensors*, including the pelvis, left and right hand, left and right feet, and head.

4.3.7.1.2.4 Option D

In this option, we deleted the left and right hand, left and right foot, a total of four sensors. We considered the remaining *eight sensors*, including the pelvis, left and right shank, left and right forearm, torso, C5 and head.

The alternatives are illustrated in Figure 4-13 and subjected to testing using the model CNN-LSTM option 2. The results are presented in Section 5.2.4.2

Chapter 5. Results

This chapter presents the results of the methodologies mentioned in Chapter 4. First, Section 5.1 displays the results of the comparison between two types of wearables devices for acquisition and how impact the sliding window segmentation techniques in the performance of Deep Learning methods.

Second, Section 5.2 presents the results of the methodology used in the applied case mentioned in Chapter 4. It includes a summary of the mini-BESTest evaluation, and the AI methodologies used to explore the differences between IMUs data, and the evaluation made by a professional. The text compares data from IMUs previously labeled with the test's evaluations made by professionals and includes a test evaluation to observe the behavior of blind and sighted tested groups.

5.1 IMU's vs. MOCAP and Sliding Window Variation

In this section are displayed the results of comparing IMU's and MOCAP with doing HAR and to find which is the most appropriate window size to obtain acceptable performance metrics with a low inference time.

Firstly, a window size of 100 was tested considering the same frequency rate that was used to record the three activities. Secondly, the window size was doubled (200 frames) and after that, the window size decreased using 75 and 50 samples. Due to there not being relevant changes in accuracy and the F1-score (see Table 5-1) using the long ones, a reduction in window size was registered using shorter (25, 20, 15, 10, 5).

For IMU data, the accuracy obtained surpasses 90.08% using a window of 20 frames in advance, as shown in Table 5-2 Table 5-4. Moreover, this result is better using the two last architectures: the LSTM and the hybrid model, which both achieve 99%. On the other hand, for the F1-score, an increment is observed using a window of 20 frames which is around 83.35%. For the simplest networks (DNN and CNN) as the size of the window is smaller (5, 10, 15) accuracy and F1-score are not high enough which would affect final predictions.

Table 5-1. Performance Metrics in Window Sizes of 200, 100, 75, and 50 for IMU and MOCAP.

Model	IMU 200		IMU 100		IMU 75		IMU 50	
	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
DNN	0.99	95.64	0.99	91.85	0.99	89.38	0.98	88.41
CNN	0.99	94.91	0.98	91.35	0.97	92.66	0.94	90.36
LSTM	0.94	95.95	0.99	91.85	0.99	92.34	0.99	88.79
CNN-LSTM	0.99	96.84	0.99	99.97	0.99	91.17	0.99	90.82

Model	MOCAP 200		MOCAP 100		MOCAP 75		MOCAP 50	
	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
DNN	1	89.07	0.99	87.19	0.99	86.43	0.99	83.89
CNN	0.99	89.49	0.98	86.3	0.98	88.6	0.96	87.57
LSTM	0.99	89.75	0.99	87.83	1	88.08	0.99	85.96
CNN-LSTM	0.99	89.89	0.99	88.63	0.99	88.14	0.99	86.20

Regarding MOCAP data (see Table 5-2) accuracy is above 87% using windows from 10 frames to 25. Being 20 frames, which achieves 99% for LSTM and 98.88% for CNN-LSTM. For the F1-score, the window which comprises the 20 frames results in 82.80% using the CNN-LSTM model. The sliding windows smaller than 20 (15, 10, 5) have an F1-score below 80%, therefore the prediction will be affected and won't have high accuracy.

Moreover, Table 5-3 illustrates the precision, recall, and F1-score metrics values for the four deep learning algorithms corresponding to each window size. As a result, a window of 20 frames presents a precision between 85 and 87%.

Furthermore, Table 5-4 presents the sensitivity and specificity of the four DL architectures tests. As is shown in Table 5-4 the window of 20 frames presents a sensitivity between 83 and 87%, and specificity from 91 to 93%.

Table 5-2. Performance Metrics in Window Sizes of 5, 10, 15, 20, and 25 for IMU and MOCAP.

Model	IMU 5		IMU 10		IMU 15		IMU 20		IMU 25	
	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
DNN	0.86	79.53	0.89	80.7	0.91	81.68	0.94	83.36	0.96	82.72
CNN	0.82	79.74	0.87	83.59	0.89	84.76	0.9	88.01	0.92	88.87
LSTM	0.91	80.8	0.96	82.22	0.99	83.47	1	85.18	1	86.93
CNN-LSTM	0.89	83.56	0.95	84.57	0.98	85.4	0.99	87.08	1	87.5

Model	MOCAP 5		MOCAP 10		MOCAP 15		MOCAP 20		MOCAP 25	
	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
DNN	0.86	77.73	0.89	77.64	0.94	78.75	0.94	78.31	0.96	81.19
CNN	0.81	76.19	0.87	79.56	0.89	81.7	0.92	82.74	0.93	83.67
LSTM	0.93	74.6	0.96	77.48	0.99	78.6	1	80.57	1	82.21
CNN-LSTM	0.89	79.94	0.95	80.06	0.97	81.37	0.99	82.8	0.99	84.36

Table 5-3. Recall and Precision for IMU and MOCAP.

Model	IMU 5		IMU 10		IMU 15		IMU 20		IMU 25	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
DNN	80.56	79.14	81.62	80.51	82.45	81.60	83.45	83.27	83.07	82.55
CNN	80.73	79.37	84.27	83.28	85.79	84.63	85.18	87.81	89.26	88.69
LSTM	81.08	80.60	82.30	82.16	83.89	83.67	85.17	85.19	87.00	86.88
CNN-LSTM	83.80	83.45	84.82	84.48	85.47	85.19	87.23	87.83	87.64	87.44

Model	MOCAP 5		MOCAP 10		MOCAP 15		MOCAP 20		MOCAP 25	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
DNN	78.40	77.40	79.89	77.32	80.5	78.44	81.53	78.18	83.03	81.01
CNN	78.23	75.73	81.4	79.04	82.5	81.36	84.50	82.34	85.24	83.32
LSTM	76.56	74.23	79.78	77.15	81.41	78.45	83.56	80.29	84.62	82.06
CNN-LSTM	81.25	79.56	82.21	79.74	83.38	81.08	84.55	82.57	85.75	84.14

Model	IMU 200	IMU 100	IMU 75	IMU 50
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	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
DNN	95.68	95.64	91.84	91.86	89.67	89.29	88.46	88.43
CNN	94.90	94.92	91.43	91.34	92.68	92.66	90.53	90.32
LSTM	96.14	95.93	91.84	91.86	92.44	92.32	88.84	88.76
CNN-LSTM	96.84	96.84	99.97	99.97	91.20	91.15	90.98	90.75
Model	MOCAP 200		MOCAP 100		MOCAP 75		MOCAP 50	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
DNN	90.93	88.92	89.25	87.01	88.60	86.26	86.15	83.73
CNN	91.38	89.31	89.45	86.07	89.94	88.46	88.73	87.34
LSTM	92.05	89.68	90.28	87.61	89.96	87.89	87.96	85.80
CNN-LSTM	91.57	89.70	90.49	88.41	89.92	82.21	88.41	85.98

Table 5-4. Sensitivity and Specificity for IMU and MOCAP.

Model	IMU 5		IMU 10		IMU 15		IMU 20		IMU 25	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
DNN	0.79	0.90	0.81	0.90	0.82	0.91	0.83	0.92	0.83	0.91
CNN	0.79	0.90	0.83	0.92	0.85	0.92	0.88	0.94	0.89	0.94
LSTM	0.81	0.90	0.82	0.91	0.84	0.92	0.85	0.93	0.87	0.93
CNN-LSTM	0.83	0.92	0.84	0.92	0.85	0.93	0.87	0.94	0.87	0.94
Model	MOCAP 5		MOCAP 10		MOCAP 15		MOCAP 20		MOCAP 25	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
DNN	0.77	0.89	0.77	0.89	0.79	0.90	0.78	0.89	0.81	0.91
CNN	0.76	0.88	0.79	0.90	0.79	0.90	0.82	0.91	0.79	0.90
LSTM	0.74	0.87	0.77	0.89	0.78	0.89	0.80	0.90	0.77	0.89
CNN-LSTM	0.80	0.90	0.80	0.90	0.81	0.91	0.83	0.91	0.80	0.90
Model	IMU 200		IMU 100		IMU 75		IMU 50			
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity		
DNN	0.96	0.98	0.92	0.96	0.89	0.95	0.88	0.94		
CNN	0.95	0.97	0.91	0.96	0.93	0.96	0.90	0.95		

LSTM	0.96	0.98	0.92	0.96	0.82	0.91	0.89	0.94
CNN-LSTM	0.97	0.98	1.00	1.00	0.91	0.96	0.91	0.95
Model	MOCAP 200		MOCAP 100		MOCAP 75		MOCAP 50	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
DNN	0.89	0.94	0.87	0.94	0.86	0.93	0.84	0.92
CNN	0.89	0.95	0.86	0.93	0.88	0.94	0.87	0.94
LSTM	0.90	0.95	0.88	0.94	0.88	0.94	0.86	0.93
CNN-LSTM	0.90	0.95	0.88	0.94	0.88	0.94	0.86	0.93

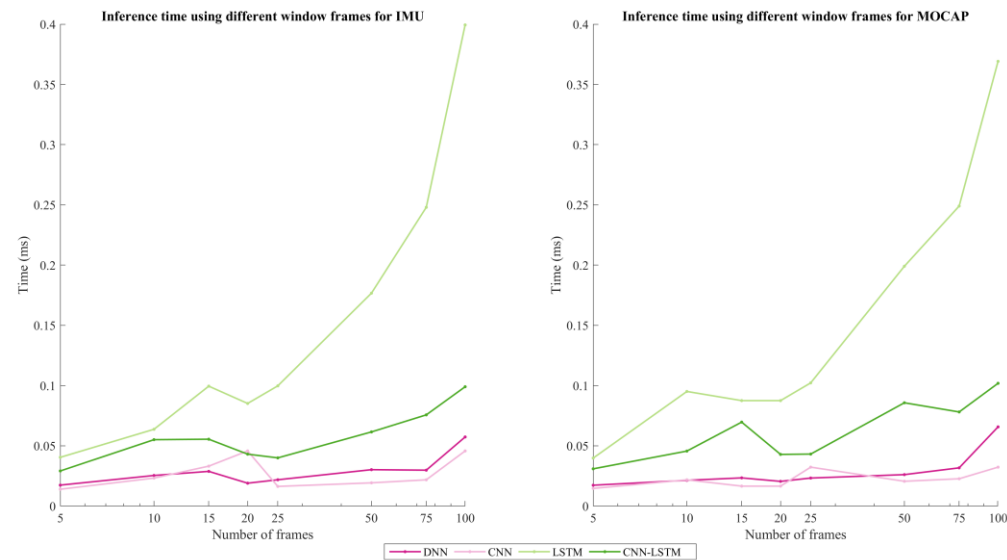


Figure 5-1. Inference Time comparison using different Windows frames for IMU and MOCAP.

In addition, inference time was calculated using an HP OMEN laptop with an AMD Ryzen 7 4800H processor with Radeon Graphics 2.90 GHz. Also, it counts with 16GB RAM. The inference time for all the window sizes was always under 1 ms. The LSTM model took more time: around 0.4 ms using 100 frames and below 0.1 ms for a window size of 20; followed by the hybrid model CNN-LSTM, CNN, and finally the DNN. Figure 5-1 shows the inference time results using the different window sizes (5, 10, 15, 20, 25, 50, 75, and 100) for each DL architecture. A disruption is observed on the window of size 15 for the LSTM model. Also, in the window of 20 frames, the CNN architecture experienced an increase too, but the rest of the architectures presented a decrease in this window size. On the other hand, for MOCAP, a disruption is observed on window size = 15 for the CNN-LSTM model, and a decrease is noted for 20 frames in all the architectures. However, a trend is maintained, which means that as the window size (the number of frames) increases, the inference time will increase.

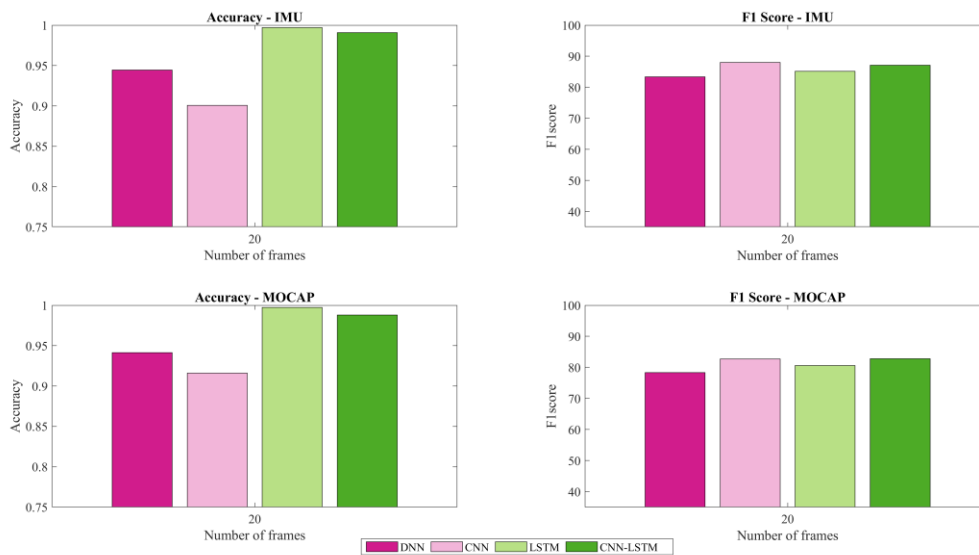


Figure 5-2. Accuracy and F1-score for IMU and MOCAP using a Sliding Window of size 20.

Finally, a sliding window of 20 frames in data acquired using a sampling frequency of 100Hz is the minimal size for obtaining a high accuracy (99 % and 98% for LSTM and CNN-LSTM), acceptable F1-score (85.18% and 87.07%), and with a low inference time (below 1 ms) for HAR of 3 activities: walking, sit-to-stand, and squatting. Despite two similar movements (sit-to-stand and squatting) were

selected, the neural networks were able to distinguish between them and classify them properly.

Figure 5-2 presents the accuracy and F1-score for IMU and MOCAP, using a sliding window of 20 frames.

Figure 5-3 presents the effectiveness and efficiency of DL models varying window sizes.

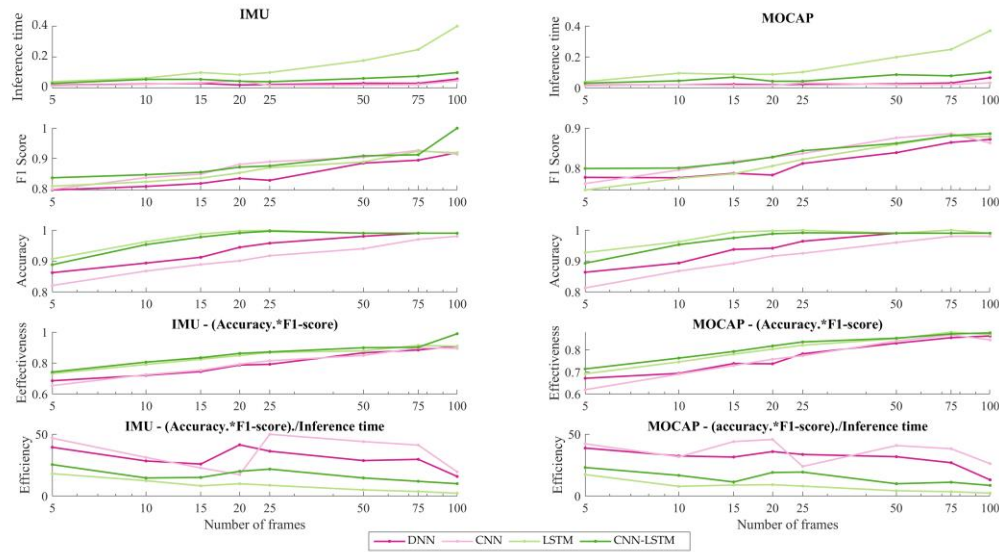


Figure 5-3. IMU vs MOCAP. (1) Inference time. (2) F1-score. (3) Accuracy. (4) Effectiveness. (5) Efficiency.

5.2 Applied Case – in VIP

The results of all the methodologies mentioned in Section 4.3.6 about the mini-BESTest implementing with AI are shown below.

5.2.1 Mini-BESTest Evaluation and Cohen’s Kappa Calculations

In the present study, the mini-BESTest was evaluated by two raters: a physiotherapist and a PhD professor. The participants' videos were used for evaluation purposes, and after completion of the assessment, the Cohen's Kappa concordance index was calculated for all fourteen activities included in the mini-BESTest. The results demonstrated a highly satisfactory Cohen Kappa index of 0.87, as shown in Table 5-5.

Table 5-5. Kappa's Table

Test number	Cohen's Kappa
1	1
2	0.869
3	0.879
4	0.782
5	0.768
6	0.847
7	1
8	1
9	1
10	1
11	0.820
12	1
13	0.463
14	0.751
Average	0.870
Concordance force	Very Good

The punctuation used in the subsequent data analysis was determined by Evaluator 1, as the concordance with Evaluator 2 is highly satisfactory.

Additionally, the evaluation of mini-BESTest made by Evaluator 1 is shown in Table 5-6 and Table 5-7.

Table 5-6. mini-BESTest Evaluation Table – Part 1.

Subject	Test 1	Test 2	Test 3	Test 3 final	Anticipatory	Test 4	Test 5	Test 6	Reactive Postural Control
S00	2	2	D- 2/I-2	2	6	1	1	D- 1/I-1	3
S01	2	2	D- 1/I-2	1	5	2	1	D- 1/I-1	4
S02	2	2	D- 2/I-2	2	6	2	2	D- 1/I-1	5
S03	2	1	D- 2/I-2	2	5	1	1	D- 2/I-2	4
S04	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6
S05	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6
S06	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6
S07	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6

S08	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6
S09	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6
S10	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6
S11	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6
S12	2	2	D- 2/I-2	2	6	2	1	D- 1/I-1	4
S13	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6
S14	2	2	D- 2/I-2	2	6	2	1	D- 2/I-2	5
S15	2	2	D- 0/I-0	0	4	2	1	D- 1/I-0	3
S16	2	1	D- 2/I-0	0	3	2	2	D- 2/I-2	6
S17	2	2	D- 2/I-2	2	6	2	1	D- 1/I-1	4
S18	2	2	D- 2/I-1	1	5	2	2	D- 2/I-2	6
S19	2	2	D- 1/I-2	1	5	2	1	D- 1/I-1	4
S20	2	2	D- 2/I-1	1	5	1	1	D- 1/I-1	3
S21	2	2	D- 0/I-0	0	4	2	2	D- 1/I-2	5
S22	2	1	D- 0/I-0	0	3	2	1	D- 2/I-1	4
S23	2	2	D- 1/I-1	1	5	2	1	D- 2/I-2	5
S24	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6
S25	2	1	D- 1/I-1	1	4	2	2	D- 2/I-2	6
S26	2	2	D- 0/I-0	0	4	2	2	D- 2/I-2	6
S27	2	1	D- 1/I-0	0	3	2	2	D- 2/I-2	6
S28	2	2	D- 2/I-2	2	6	2	2	D- 2/I-2	6

Table 5-7. mini-BESTest Evaluation Table – Part 2.

Subject	Test 7	Test 8	Test 9	Sensorial Orientation	Test 10	Test 11	Test 12	Test 13	Test 14	Dynamic Gait	mini- BESTest Score
S00	2	2	2	6	2	2	2	2	2	10	25
S01	2	2	2	6	2	2	2	2	2	10	25
S02	2	2	2	6	2	2	2	2	2	10	27
S03	2	2	2	6	2	1	2	2	1	8	23
S04	2	2	2	6	2	2	2	2	2	10	28
S05	2	2	2	6	2	2	2	2	2	10	28
S06	2	2	2	6	2	2	2	2	2	10	28
S07	2	2	2	6	2	2	2	2	2	10	28
S08	2	2	2	6	2	2	2	2	2	10	28
S09	2	2	2	6	2	2	2	2	2	10	28
S10	2	2	2	6	2	2	2	2	2	10	28
S11	2	2	2	6	2	2	2	2	2	10	28
S12	2	2	2	6	2	2	2	2	2	10	26
S13	2	2	2	6	2	2	2	2	2	10	28
S14	2	2	2	6	2	2	2	2	1	9	26
S15	2	2	2	6	2	1	2	1	1	7	20
S16	2	2	2	6	1	1	1	2	1	6	21
S17	2	2	2	6	2	2	2	2	1	9	25
S18	2	2	2	6	2	1	2	2	1	8	25
S19	2	2	2	6	2	1	2	2	2	9	24

S20	2	2	2	6	2	2	2	2	2	10	24
S21	2	2	2	6	2	0	2	2	1	7	22
S22	2	2	2	6	2	2	2	1	1	8	21
S23	2	2	2	6	2	1	2	2	2	9	25
S24	2	2	2	6	2	2	2	2	2	10	28
S25	2	2	2	6	2	2	2	2	2	10	26
S26	2	2	2	6	2	2	2	2	1	9	25
S27	2	2	2	6	2	1	2	2	2	9	24
S28	2	2	2	6	2	2	2	2	2	10	28

In Figure 5-4 is shown the fourteen activities of mini-BESTest, and their punctuation per participant. In addition, Figure 5-5 displays the histogram for each of the four parts that the mini-BESTest is divided into.

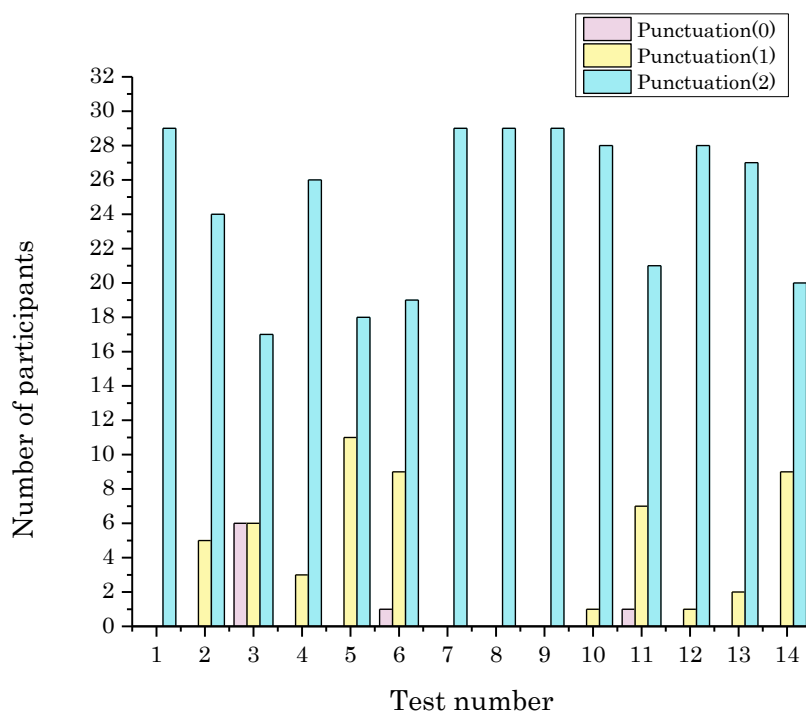


Figure 5-4. Frequency of Test 3 punctuation.

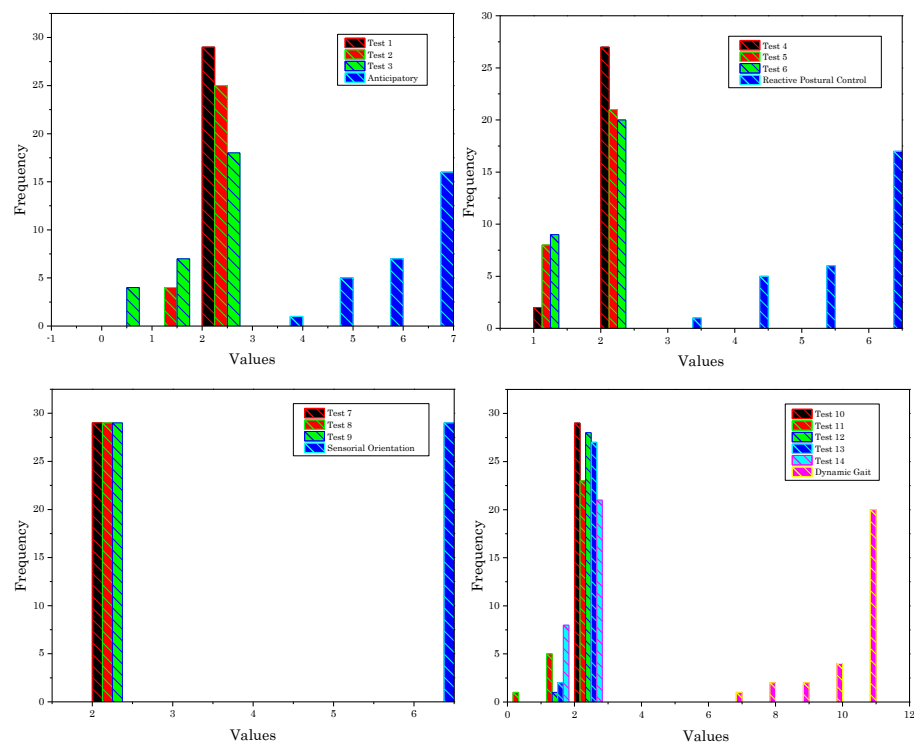


Figure 5-5. Histogram of mini-BESTest Activities by Part Test.

The activity chosen for classifying the punctuation was Test 3 due to the variability of samples. In other words, there are samples corresponding to rank 0, 1 and 2 shown in Figure 5-6.

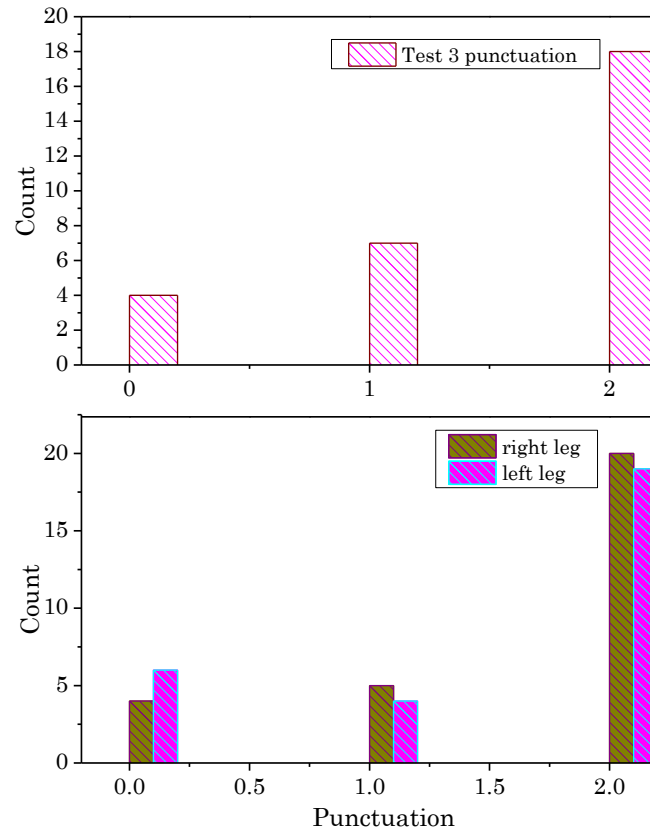


Figure 5-6. Histogram of Test 3. a) Test 3 Punctuation of Both Legs. B) Test 3 Punctuation per Leg.

5.2.2 Correlation

The correlation matrix is displayed in Figure 5-7. The variable with the highest correlation coefficient (above 0.9) was 'Anticipatory'. Additionally, variables that are constant, meaning they do not vary, were discarded. The remaining variables that are not considered are presented in histograms in Figure 5-7: 'Test 1', 'Test 4', 'Test 5', 'Test 6', 'Reactive Postural Control', 'Test 7', 'Test 8', 'Test 9', and 'Sensorial Orientation'.

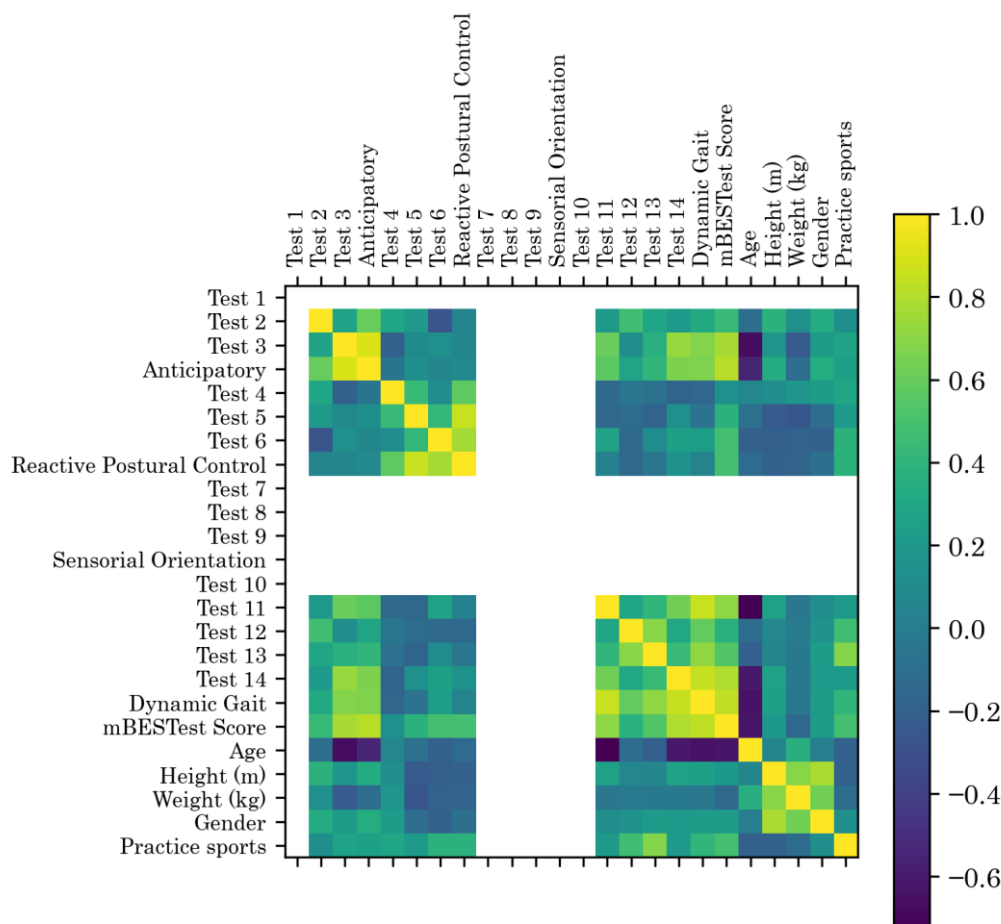


Figure 5-7. mini-BESTest - Important Variables – Correlation Matrix.

5.2.3 Machine Learning - Clustering

This text analyzes the differences between sighted and blind individuals when performing the mini-BESTest. The database is filtered by 'Blindness' and the remaining features are evaluated after the correlation study. Figure 5-8 displays the partial test, which indicates that blind individuals have less balance. Specifically, the Anticipatory and Postural Control components show the most variability in the test. Furthermore, both blind and sighted individuals received the same evaluation of 6 in Sensory Orientation, indicating no significant differences in their static balance. Additionally, in terms of Dynamic Gait, sighted individuals did not experience any issues, whereas blind individuals did not perform as well.

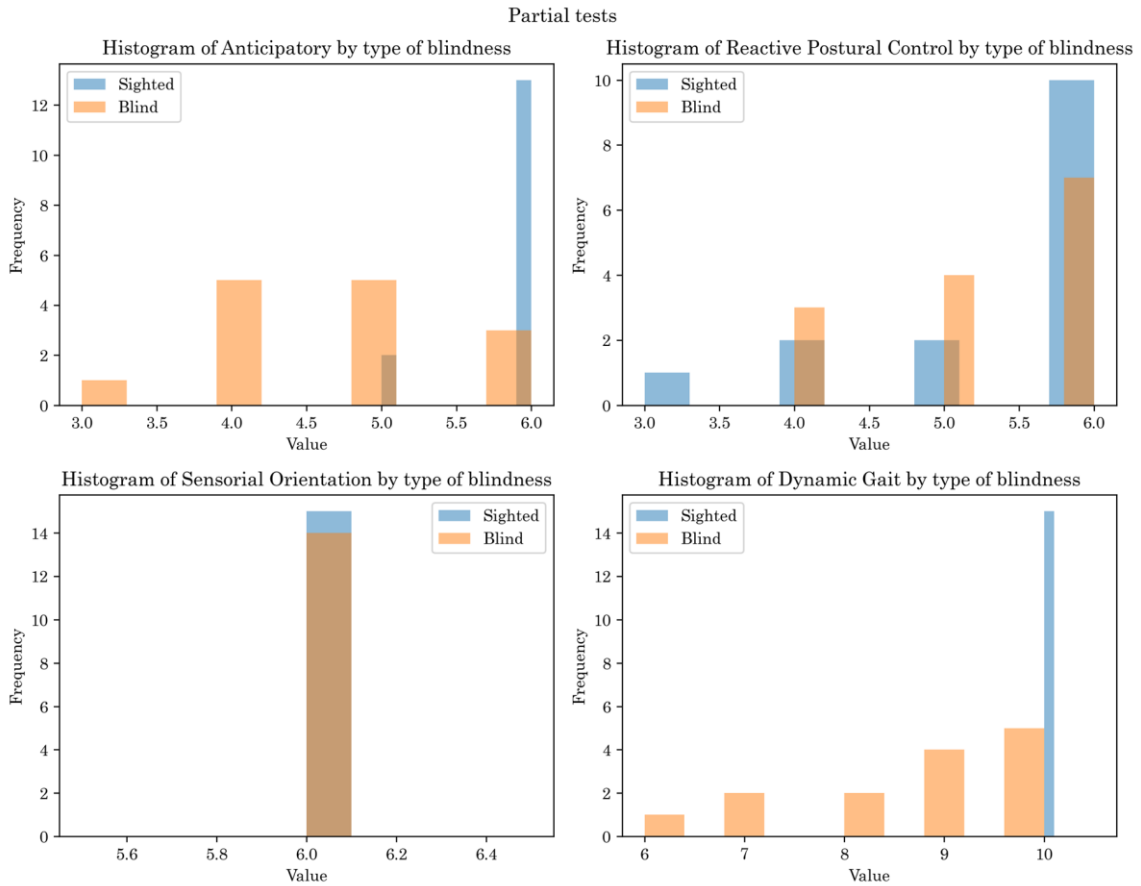


Figure 5-8. Partial Test – mini-BESTest.

For clustering, we included features such as age, height, weight, and participation in sports, as well as the remaining activities from the mini-BESTest after the correlation study in 5.1. We performed feature selection using RFE with linear regression, and then used K-Means to find the number of clusters.

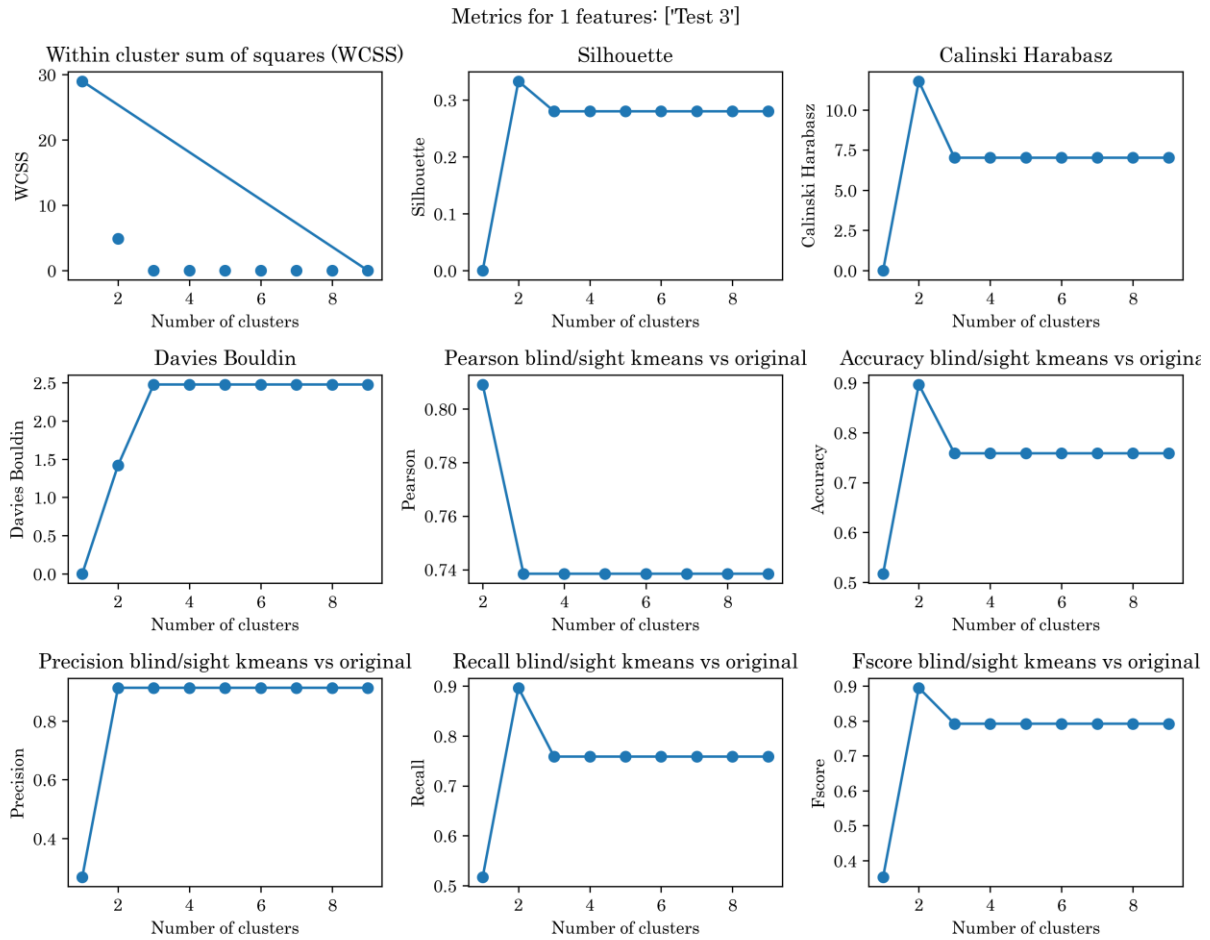


Figure 5-9. Clustering Metrics for 1 Feature.

The results using one feature are shown in Figure 5-9. Regarding clustering, using Test 3 as feature selected, we obtained 2 clusters corresponding to blind and sighted according to the elbow method mentioned above. In addition, the clustering performance metrics for two clusters such as accuracy, precision, recall and F-score are 90%, in other words, the model can perfectly discriminate these two groups.

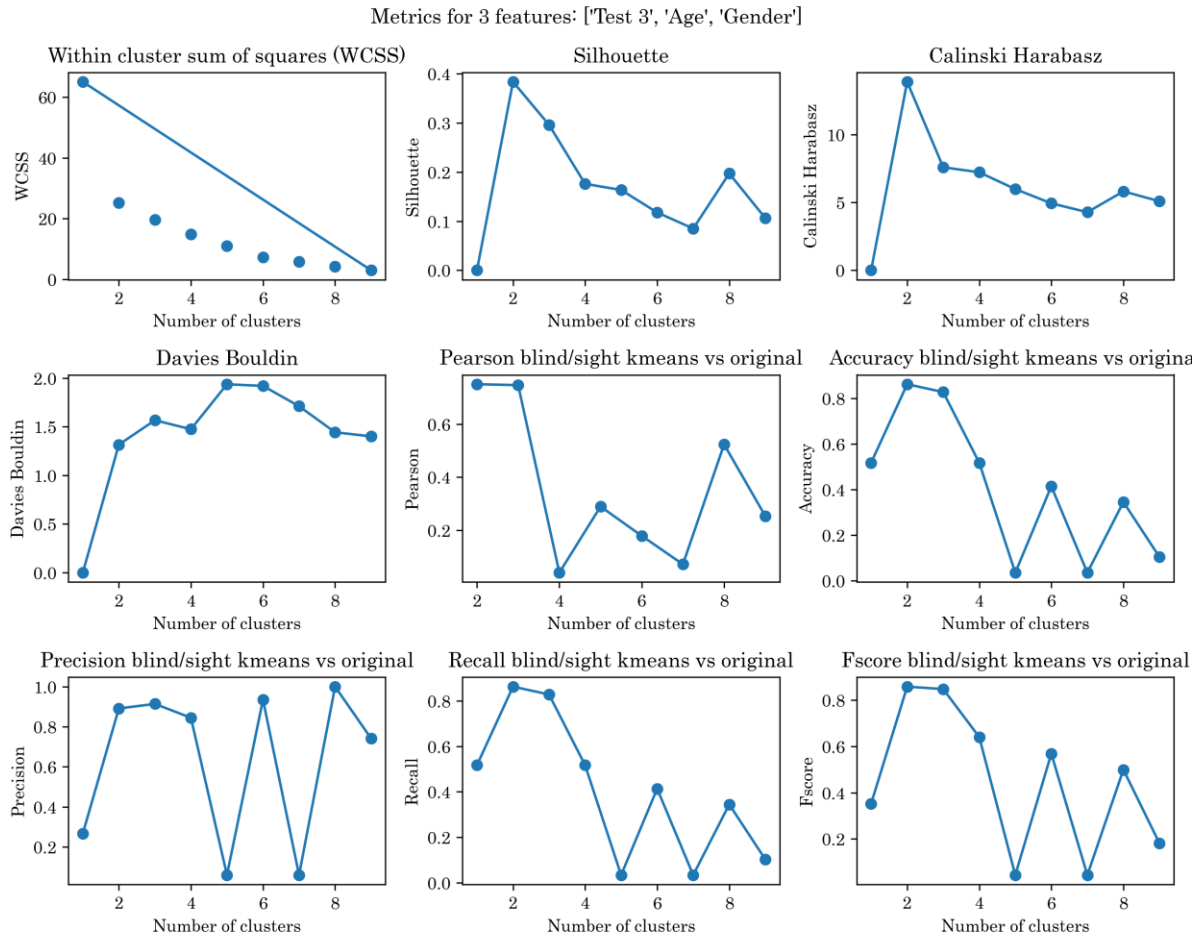


Figure 5-10. Clustering Metrics for Three Features.

Considering the first best features such as: Test 3, age, and gender. In Figure 5-10 you can see in the first three graphs the same result: 2 clusters differentiated. In addition, clustering metrics such as WCSS, Silhouette coefficient, Calinski Harabasz, Davies Bouldin and Pearson coefficient were calculated. For WCSS the low value is the best, therefore for 2 clusters is around 60; for Calinski Harabasz coefficient while closer to 1 is better differentiating clusters, for Silhouette the value is 0.4 the high value close to 1; and finally, Davies Bouldin, the low value is 1.4 corresponding to a cluster of 2.

All the clustering metrics results are shown in Appendix D.

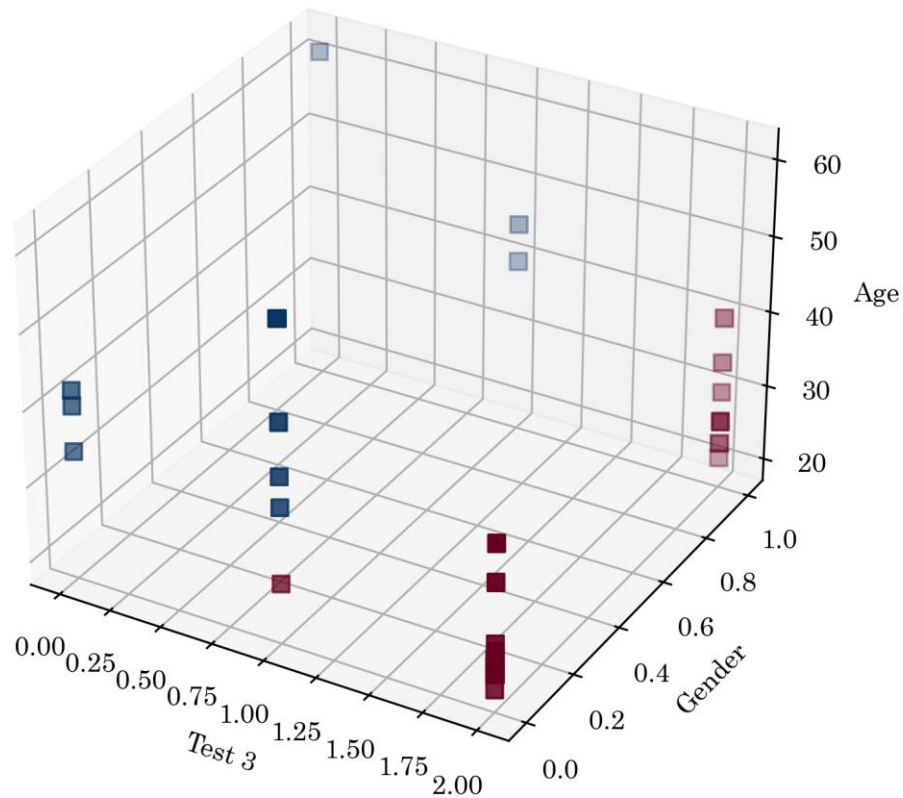


Figure 5-11. Clustering Blindness in mini-BESTest.

In Figure 5-11, the two clusters appear considering the three most important characteristics: Test 3, gender, and age. Additionally, it shows the difference between blind (blue) and sighted (red). As a result, we have found that only by performing Test 3 we can know whether a participant is blind or not.

5.2.4 Deep Learning - Classification

As previously stated in Section 4.3.7.1.1 the selected activity for the classification of the test punctuation was Test 3 due to the variability of the samples. In other words, there are samples corresponding to punctuation 0, 1, and 2, which represent the categories of bad, mild, and good punctuation. Figure 5-12 illustrates the relationship between sighted and blind individuals in terms of punctuation when they perform Test 3.

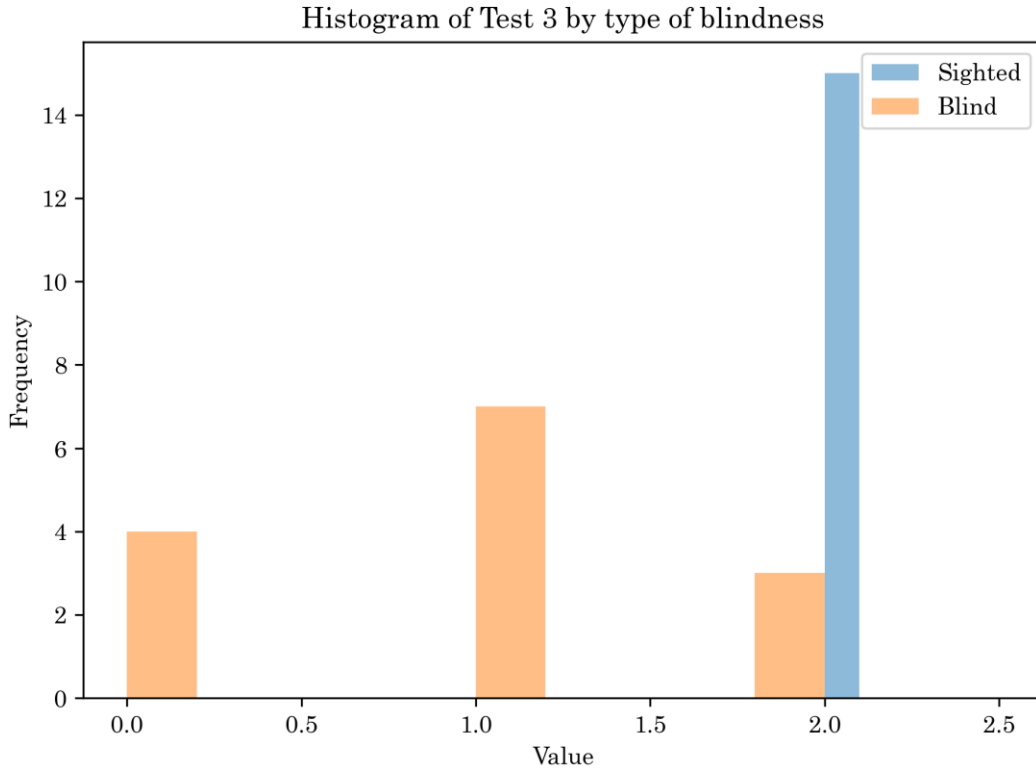


Figure 5-12. Histogram of Test 3 by Type of Blindness.

In the context of Test 3, the total number of sighted individuals was evaluated with the highest value, indicating a good balance. In contrast, the blind individuals demonstrated a range of balance, including bad, mild, and good balance.

5.2.4.1 Input Data Methodologies

5.2.4.1.1 Input Data Methodology 1

For our *first experiment*, we attempted to use an 80/20 train-test split for validation (23 people for training/validation, and 6 people for test). However, the results of multiclass classification for acceleration, acceleration + gyroscope, and quaternions did not make sense, despite accuracy being above 90%. We suspect that some information from the training data may have been included in the validation set. As a result, we conducted a *second experiment* using Nested Cross Validation to verify the model's performance, given our limited dataset. Also, we evaluated three DL architectures: CNN-ID, LSTM and CNN-LSTM (opt.1) using two types of activation functions: ReLU and sigmoid and a multiclass classification was done.

The results using quaternions as input data are presented in Table 5-8 and Table 5-9. First including ReLU as activation function and the second sigmoid.

Table 5-8. Performance Metrics for Nested Cross-Validation using Quaternions as Input Data and ReLU as Activation Function.

Input data type	Sliding window size	Model	Performance metrics				
			Average Performance ReLU	Standard deviation	F1-score	Macro F1-score	Weighted_F1-score
Quaternions	25	CNN-ID	0.539	0.135	[2.303e-01 1.471e-04 6.885e-01]	0.306	0.176
Quaternions	25	LSTM	0.516	0.158	[0.160 0.019 0.668]	0.283	0.160
Quaternions	25	CNN-LSTM (opt.1)	0.618	0.196	[0.166 0.154 0.743]	0.354	0.239

5-8 Type of Classification: Multiclass Classification

Table 5-9. Performance metrics for Nested Cross-Validation using Quaternions as Input Data and Sigmoid as Activation Function.

Input data type	Sliding window size	Model	Performance metrics				
			Average Performance Sigmoid	Standard deviation	F1-score	Macro F1-score	Weighted_F1-score
Quaternions	25	CNN-ID	0.577	0.172	[0.223 0.111 0.701]	0.345	0.207
Quaternions	25	LSTM	0.593	0.076	[1.478e-01 1.812e-04 7.441e-01]	0.297	0.181
Quaternions	25	CNN-LSTM (opt.1)	0.510	0.148	[1.555e-01 3.945e-04 6.537e-01]	0.270	0.139

5-9 Type of Classification: Multiclass Classification

Additionally, we investigated *alternative options*. Since to the model's inability to distinguish between 2 (bad) and 1 (mild) accurately, we suggested trying *binary classification* instead of multiclass classification. For this, we evaluated two options:

- Option A: changing the 1's to 0 and the 2's to 1.

- Option B: involves changing the 2's to 1.

The results are presented in Table 5-10, and it were considered quaternions and acceleration as input data. Additionally, it was tested on the CNN-LSTM option 1.

Table 5-10. Binary Classification results for Input Methodology 1, Quaternions and Acceleration Data.

Input data type	Window size	Model	Option	Average Performance ReLU	Standard Deviation ReLU	Avg. F1-Score	Avg. Macro F1-score	Avg. Weighted F1-score
Quaternions	25	CNN-LSTM (opt. 1)	A	0.579	0.141	[0.196 0.710]	0.453	0.276
Quaternions	25	CNN-LSTM (opt. 1)	B	0.834	0.102	[0.117 0.906]	0.512	0.444
Acceleration	25	CNN-LSTM (opt. 1)	A	0.666	0.130	[0.249 0.776]	0.512	0.349
Acceleration	25	CNN-LSTM (opt. 1)	B	0.886	0.126	[0.367 0.934]	0.650	0.593

⁵⁻¹⁰ Type of Classification: Binary Classification

Finally, we attempted *data augmentation* and *balanced the dataset* distributing the data with more frequency into train, validation, and test, but the results were not accurate, not surpassing 60% of accuracy average.

5.2.4.1.2 Input Data Methodology 2

Since there was no improvement in the performance of the neural network using input data methodology 1, we proceeded to evaluate the second approach. This entailed analyzing the information and the scores of each leg separately, meaning that the evaluation made for each leg before the final one remained unchanged.

Additionally, we considered two options as input data to test the model's prediction accuracy: raw acceleration and quaternions. This decision was made to analyze the model's performance with less feature-rich data and to compare the results between raw acceleration and quaternions. Because quaternions involve more data processing.

Four DL models were tested: CNN, LSTM, GRU, and two variations of the hybrid model - CNN-LSTM (option 1 and 2, 1 being the complex and 2 corresponds to the light one). The results are displayed in Table 5-11.

Table 5-11. Multiclass Classification results for Input Methodology 2, Acceleration Data.

Input data type	Sliding window size	Model	Performance metrics				
			Average Performance ReLU	Standard deviation	F1-score	Macro F1-score	Weighted_F1-score
Acceleration	25	CNN-ID	0.749	0.064	[0.481 0.208 0.855]	0.515	0.388
		LSTM			[0.509 0.299 0.894]		
Acceleration	25	GRU	0.804	0.040	[0.596 0.250 0.889]	0.567	0.460
Acceleration	25	GRU	0.795	0.057	[0.596 0.250 0.889]	0.578	0.465
Acceleration	25	CNN-LSTM (opt.1)	0.811	0.101	[0.559 0.387 0.894]	0.613	0.510
Acceleration	25	CNN-LSTM (opt.2)	0.817	0.061	[0.480 0.329 0.900]	0.612	0.507
Acceleration	50	CNN-LSTM (opt.1)	0.812	0.076	[0.552 0.213 0.907]	0.570	0.465
Acceleration	50	CNN-LSTM (opt.2)	0.814	0.036	[0.465 0.338 0.906]	0.570	0.467

⁵⁻¹¹ Type of Classification: Multiclass Classification

The selected DL architecture is the hybrid CNN-LSTM option 2. The performance metrics for options 1 and 2 were nearly identical despite the sliding window variation. The model accuracy and F1-score for CNN-LSTM option 2 with a SL of 25 gave the best F1-score. This architecture is used for the rest of the experiments. A nested cross-validation was also employed, and the experiment was repeated five times to analyze the variation. The input data was either option A (acceleration) or option B (quaternions).

5.2.4.1.2.1 Option A: Acceleration as an Input Data

Experiment 1: Multiclass Classification

This classification considers three labels as classes: 0, 1, and 2, which correspond to bad, mild, and good evaluations, respectively. The model selected was CNN-LSTM (option 2).

Table 5-12. Model Selected: CNN-LSTM (opt.2)

Experiment	Average Performance ReLU	Standard Deviation ReLU
1	0.778	0.067
2	0.829	0.042
3	0.842	0.067
4	0.773	0.053
5	0.834	0.051
Average	0.811	0.056

Table 5-13. Best Experiment (number 3)

Fold	F1-score	Macro_F1-score	Weighted_F1-score
0	[0.652 0.780 0.989]	0.807	0.758
1	[0.308 0.329 0.901]	0.513	0.422
2	[0.785 0.666 0.918]	0.790	0.689
3	[0.502 0. 0.915]	0.472	0.386
4	[0.469 0.010 0.892]	0.457	0.347
Average	[0.543 0.357 0.923]	0.608	0.520

The F1-score indicates the model's ability to correctly identify good (2) and bad (0) evaluations but struggles with mild (1) evaluation as shown in Table 5-13. Therefore, we propose conducting an additional experiment using binary classification with two options: Option A involves grouping 1s with 0s and 2s with 1s, while Option B involves grouping 2s with 1s and leaving 0s as they are.

Experiment 2: Binary Classification

Binary classification involves only two parameters: 0 and 1, corresponding to 'bad' and 'good' evaluations. Two options are available for this type of classification:

Option A: involves changing 1 to 0 and 2 to 1, while

Option B: involves changing 2 to 1.

Table 5-14 displays the results of binary classification.

Table 5-14. Binary Classification results for Acceleration Data.

Option	Average (accuracy) Performance ReLU	Standard Deviation ReLU	Avg. F1-Score	Avg. Macro F1-score	Avg. Weighted F1-score
A	0.773	0.197	[0.449 0.798]	0.623	0.477
B	0.851	0.102	[0.201 0.914]	0.557	0.476

Finally, we conducted an additional experiment to improve the dataset balance and enhance performance.

Experiment 3: Data Balanced.

To ensure balance in the data, we excluded participants (9, 5, 4, 3) who received a score of 2, as it was the most frequent class. The model was then tested with the remaining participants, and the performance metrics with this variation are displayed in Table 5-15.

Table 5-15. Results with Data Balanced.

Participants excluded	Average (accuracy) Performance ReLU	Standard Deviation ReLU	Avg. F1-Score	Avg. Macro F1-score	Avg. Weighted F1-score
9	0.642	0.143	[0.495 0.297 0.753]	0.515	0.346
5	0.689	0.130	[0.498 0.234 0.800]	0.511	0.360
4	0.756	0.105	[0.562 0.229 0.873]	0.555	0.431
3	0.702	0.131	[0.504 0.295 0.811]	0.537	0.390

5.2.4.1.2.2 Option B: Quaternions as an Input Data

Table 5-16. Multiclass Classification – CNN-LSTM (opt. 2).

Experiment	Average Performance ReLU	Standard Deviation ReLU
1	0.799	0.066
2	0.785	0.085
3	0.818	0.024
4	0.781	0.070
5	0.775	0.043
Average	0.792	0.058

Table 5-17. Best Experiment (number 3).

Fold	F1-score	Macro_F1-score	Weighted_F1-score
0	[0.501 0.695 0.903]	0.700	0.588
1	[0.641 0.194 0.901]	0.579	0.480
2	[0.517 0.555 0.878]	0.650	0.524
3	[0.441 0. 0.925]	0.455	0.378
4	[0.727 0.006 0.882]	0.538	0.420
Average	[0.565 0.290 0.898]	0.584	0.478

No additional evaluations were conducted using quaternions as input data due to the negligible difference in performance metrics compared to using raw acceleration, as demonstrated in Table 5-17.

5.2.4.2 Determination of the Optimal Number of IMUs on the Body

The four alternatives above mentioned were tested using model CNN-LSTM option 2 and analyzed using as activation functions: ReLU and sigmoid.

Table 5-18. Options to Select Optimal number of IMUs on the Body.

Options	Sensors	Average Performance ReLU	Standard Deviation ReLU	Average Performance Sigmoid	Standard Deviation Sigmoid
A	7	0.702	0.099	0.758	0.109
B	7	0.794	0.038	0.789	0.044
C	6	0.800	0.055	0.799	0.045
D	8	0.728	0.083	0.728	0.092

The results are presented Table 5-18, indicating that options A and D have lower accuracy compared to options B and C. The average accuracy for options B and C is 0.794 and 0.800, respectively.

We also conducted a statistical test, specifically a *student's t-test*, to evaluate the significance of the difference between having 7 or 6 sensors, as these two options have a difference of almost 10 points compared to A and D.

In our case, we used a sample size of 5 for cross-validation. The results of Student's test give us a difference of 0.006 and a significant level of $p=0.836$. Based on these values, we cannot reject the null hypothesis that the mean difference is zero. The difference between the two groups is small, and the confidence interval includes zero, indicating that the difference is not statistically significant at the 0.05 significance level.

Additionally, the t-statistic is small, which further supports the conclusion that there is no significant difference between the groups. Even though options B and C are not significantly different, we recommend *option C* (6 sensors) to perform Test 3, as a result values will remain the same. As already mentioned above the six sensors must be placed as follows: pelvis, left and right hand, left and right foot, and head. This configuration is displayed in Figure 5-13.

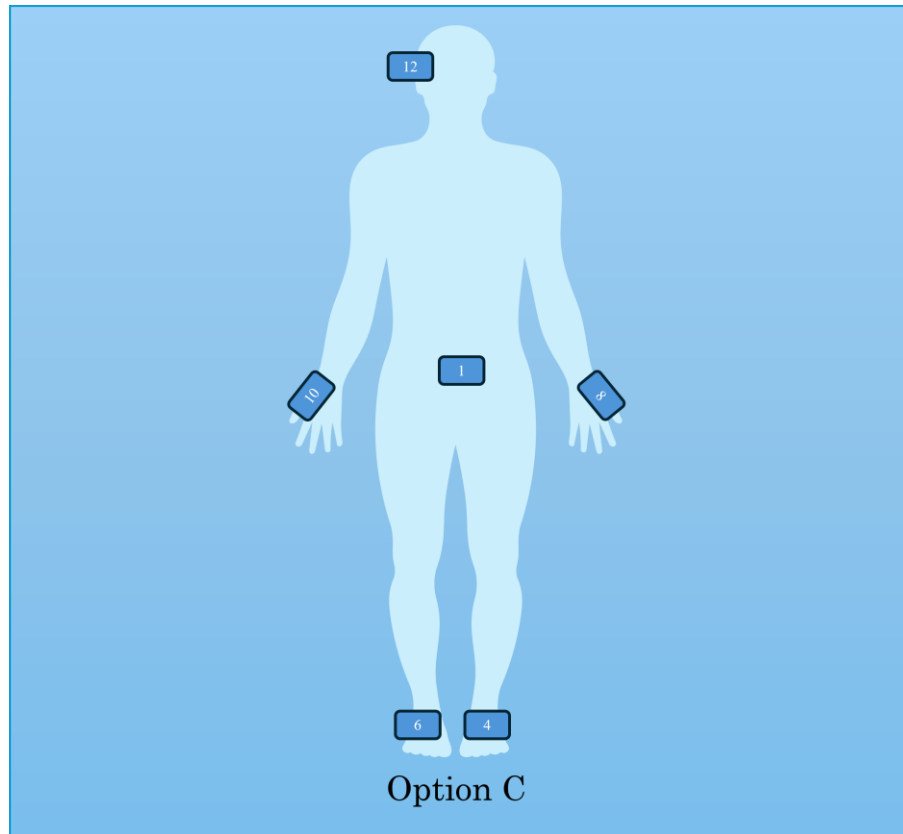


Figure 5-13. Option chosen as Optimal Number of Sensors.

Finally, the model accuracy and ROC curves per each fold are displayed in Appendix F.

Chapter 6. Discussion

The importance of sliding windows as a segmentation pre-processing tool in the input of a classification neural networks especially for doing HAR is mentioned in [112]. Most of the studies consider the sliding window method by dividing all sequences throughout time. On the contrary, this current study considered analyzing the sequence based on frames in order to make a relation with literature's terminology. In [113] Wang et al., differentiate the impact of window size for motion mode recognition and pose. For motion, increasing the window size may affect the cut-off window length and sacrifice the recognition speed. They suggest as performance requirements a cut-off length of 6s with an F1-score beyond 99%. Also, if the focus is to reduce the latency, a shortened window is needed and a reduction in accuracy is expected. For instance, a window between 2.5 - 3.5 s with an F1-score of around 95% was suggested [113]. In this current work, patterns and features have been extracted more accurately using LSTM and CNN-LSTM. Also, the indicator of performance reflects an F1-score that surpasses 80% for both types of data: IMU and MOCAP using a sliding window of 20 frames (see Figure 5-2) a window which is smaller than the used in [113]. A reduction of cost processing was obtained when placing the trained model in production, which is in agreement with other applications [114] where the proper selection of sliding windows (window size) is important to also ensure that clinical information due to subtle changes are captured from the analyzed signal.

Furthermore, in [115] Banos et al., says that 1 to 2 s correspond to the interval which provides the best trade-off between recognition and accuracy. Thus, this current work agrees with them because the highest accuracy was found in 100 frames or 1s. Also, that work [115] analyzed the effects of window process on activity recognition performance, thus, a reduction in window size was done obtaining the most precise recognizer for very short windows being (0.25–0.5s), the perfect interval for recognition of most activities. This study is in accordance with Banos due to 20 frames (0.20s) corresponding to the most proper window size for the recognition of these three activities (walking, sit-to-stand, and squatting).

Regarding other approaches to preprocess the data, in [116] Golamiangonabadi et al., mentioned that the features were obtained using four pre-processing scenarios: using vector magnitude, sliding windows, vector magnitude and applying sliding window to this data, and without any pre-processing. It concluded that the

accuracy increased with the incrementation of the value of sliding windows from 5, 10, 15, 20, and 50. Also, there were considered other techniques for evaluating the model: Cross-Validation and Leave-One-Subject-Out Cross-Validation (LOSOCV). The accuracy was increased from 85% to 98% using LOSOCV. In contrast, in this study, a train-test split was used for the evaluation and the accuracy was similar to theirs.

Additionally, in [117] Abbaspour et al. have shown the performance of four DL hybrid models to do HAR. As a result, the models that include Bi-directional RNNs perform better than the uni-directional RNNs. Also, regarding sensitivity, there was not huge difference observed in all the models above 93%; however, specificity reached 99% for all the hybrid models. In contrast, this current work tested CNN-LSTM uni-directional hybrid model reaching better accuracy and F1-Score. In addition, the sensitivity for a window size of 20 in IMU was 87.03% and specificity was 93.52%.

In this study, the previous work [118] that considered a sliding window of 100 frames (1s) has been completed. Performance metrics resulted in about 88% for the F1-score but this implies more processing costs and does not vary as much as the case when using a window of 20 frames enhancing an F1-score of 82.80% for MOCAP. Moreover, for IMU data the F1-score obtained was 99% using 100 frames (1s) and 83.35% using 20 frames (0.20s). As shown in Figure 5-1, the window that presents a size of 20 has the best accuracy per inference time. Also, despite the third and fourth architectures (LSTM, CNN-LSTM) that imply more parameters resulted in the best solutions, since they have the best accuracy, and the time is still considerably low to be used in real-time.

As for the inference time, in [119] it is calculated in two of the models presented here: LSTM and CNN-LSTM. The inference times obtained were 0.0106s and 0.3941s, respectively, resulting in LSTM's is around 3X slower than CNN-LSTM's. On the contrary, in this current work, the inference time is in the order of ms and was higher for LSTM than the hybrid model CNN-LSTM, being in a window of 20, 0.0852 ms, and 0.0431 ms, respectively, which represents that LSTM is 2X faster than CNN-LSTM. Comparing 100 frames with 20 frames, using a window of 20 frames the LSTM is 4X and CNN-LSTM is 2X faster than in a window of 100 frames.

Furthermore, in order to discuss the better performance per inference time in this work, the effectiveness and efficiency of DL's models varying window sizes have

been calculated (see Figure 5-3). As is shown in Figure 5-3-4, effectiveness resulting from multiplying the performance metrics: accuracy and F1-score, is noticed that around 20 frames the accuracy surpasses 80% being LSTM as closed as CNN-LSTM architecture which this last model achieves the best accuracy for IMU. However, for MOCAP the stabilization was observed around 20 to 25 frames. Also, a disruption is reflected in 75 frames for both systems (IMU and MOCAP) due may be to this particular window size overlapping two different activities and this causes a decrease in efficacy. On another hand, in Figure 5-3-5, the efficiency which implies effectiveness per inference time, for IMU, the CNN presented the highest efficiency about 57% using 25 frames but due to the inference time is low (order of milliseconds) for the four DL architectures, the hybrid model (CNN-LSTM) is chosen as the best because its stability over time. As it is the IMU's case, for MOCAP, the CNN model presented more efficiency, but the same stabilization that is shown in IMU from 20 frames is noticeable since 25 frames for MOCAP.

Applied Case - Balance in Blind

In this section we tested two AI approaches: Machine Learning and Deep Learning.

Machine Learning: At the first approach we only analyzed the information given by the evaluation table of mini-BESTest done by two experts, one of them is a Physical therapist. Similar process did Kamran et. al [120] when a physiotherapist ranked the activities that was previously recorded in video. In our study we found that the two groups in the research could be separated when executing 1 activity of the mini-BESTest: “standing on one leg”. These results obtained by the clusters can be defended per videos when a sighted or blind person was doing the activity.

On the other hand, most research that includes balance tests and machine learning does not consider people with visual impairments and use another balance tests. Lin B. et al [121], predict Berg balance scale (BBS) score of a participant without professional supervision using Machine Learning regression and IMUs. Tim Bao et. al [122] analyze the feasibility of using trunk sway data and machine learning (ML) techniques to automatically evaluate balance, providing accurate assessments in-home.

Deep Learning: It is confirmed that using DL models we can treat the IMUs data as time series and classify the punctuation given by a professional to a balance test, being a multiclass classification to predict if the participant has bad, mild or good balance when doing Test 3 of mini-BESTest. In [102] Gil-Martín M et.al found the scoring performance of Y-Test and was treated as regression problem on the

contrary, because they wanted to obtain the normalized reach distance (NRD) per each leg.

Regarding the number of sensors in the body for this experiment, we recorded information from 12 parts of the body but also, we analyzed what would be the minimal number of sensors to obtain acceptable performance in the classification of Test 3. We reduced the number to 6 sensors. On the contrary, other studies included 1, 2 or 8 sensors depending on the activity. It could be because only with 1 sensor they could obtain one activity in its study, but our study included 14 different activities, and it was the first time we created a database with valuable information that take into account blind people.

In addition, in our study we tested 4 types of models: CNN-1D, LSTM, GRU and CNN-LSTM being the hybrid model the most accurate in classifying accuracy and F1-score. Yeon-Wook Kim et. al [123] used a CNN-ID and GRU ensemble model to assess clinical balance using BBS. They compared it to previous work that used ML instead of DL obtaining 98.4% as model best accuracy. Also, Youness et. al [124] utilized a CNN to train and extracted the weights after trained to predict fall events using the Balance Test Score.

Furthermore, the results obtained using the first methodology in DL where considered the information of the final evaluation per both legs take us to try data augmentation, but results did not surpass 60%. A data augmentation method was tried per Wei W et. al [125] to create more variable data prevenient from the Center of Mass (CoM) varying the x and z position and this with a Balance Evaluation Test to estimate the balance level of each subject if has or not fall risk.

On the other hand, the results obtained using the second methodology in DL when testing multiclass classification, we varied the sliding window from 50 to 25 and the performance metrics results similar. Also, we tested two configurations of hybrid models, the first including more layers and the second including less and the results were similar in the second configuration reaching 80% of accuracy. Another important test was comparing raw acceleration with quaternions. Results when training the CNN-LSTM option 2 model does not have a big difference, hence we finish working with acceleration.

On the other hand, when testing binary classification using acceleration or quaternions as input data that the label 2 and 1 could be confused in the prediction because a sighted difference came from an expert evaluator. It would be recommendable to be tested further to have more data cases including evaluation of 0, 1, 2 (more participants), test it again and the performance could be increased.

Chapter 7. Conclusions

Initial Methodologies to Assess Orientation and Mobility

To assess orientation and mobility, the importance of Unity as software to design applications in an environment such as video games, gives us a good tool to guide and orientate people with visual impairments.

Also, the emergence of Artificial Intelligence and computer vision generated a new approach to create apps for orientation and mobility that includes training DL models to predict the position in x and y using inertial measurements unit on the mobile phone. In addition, using images aims you can automatically train AI models to predict the Mahalanovis distance in terms of cognitive maps when helping VIP to remind objects inside a room that goes per first time.

Finally, as well as orientation and mobility, that rehabilitation field in VIP is very important as helping tools for trainers such as: study of gait velocity and the displacements made by using correctly cane techniques.

Data Acquisition Devices: IMU vs. MOCAP

The impact of using deep learning models as well as an appropriate size for the sliding window aims in the recognition of human activities and affects the cost of processing. In this study, after comparing the results for IMU and MOCAP data, it can be concluded that it is not necessary to use big sliding windows to get high-performance metrics (good prediction) because it will increment the cost of processing (inference time) and capability of the response of any application that will create using the trained model. Hence, choosing an adequate window size and the use of deep learning algorithms to interpret the sequences comprised by the 3D acceleration of each system used are important to obtain a final prediction. Regardless of the dataset used: IMU or MOCAP data, using the more specialized deep neural architectures (LSTM and CNN-LSTM) and a minimal overlapping window of 20 frames, lead to obtaining higher accuracy (above 90%), an F1-score (above 80%), and an inference time (below 0.1 ms) for both systems. Furthermore, with the usage of large sliding windows (100, 200 frames), there are almost no accuracy differences. However, small sliding windows present a decrease in the F1-score. Overall, this study presents an inference time less than 1 ms for sliding windows ranging from 5 to 100 frames (0.05 to 1s) and tested for each DL architecture such as DNN, CNN, LSTM, and CNN-LSTM. Hence, data segmented

using a sliding window of 20 frames can be preprocessed 4X (LSTM) and 2X (CNN-LSTM) faster than using 100 frames. Consequently, this low inference time is suggested for real-time applications, for instance, to detect given movements. In addition, this work has been conducted using a fixed frequency of 100 Hz. Other results will be obtained if variable frequencies are used (20, 30, and 50 Hz) because sliding windows will vary.

In summary, the comparison of these two acquisition devices, IMUs and MOCAP, indicates that the use of low-cost IMUs allows for the recognition of human activities with satisfactory performance metrics, including accuracy and F1-score, in contrast to the use of MOCAP systems, which are high-cost systems.

Applied Case in Blinds

The last part of this thesis was a novel case study to prove if using low-cost IMUs we were able to track important movements in the body and classify the evaluation made by a professional of a balance test named mini-BESTest. This test was adapted for blinds.

First, prior to utilizing the IMUs data, we conducted an initial assessment utilizing only the evaluation table for the mini-BESTest. We employed machine learning (ML) clustering, specifically K-Means, and discovered that the performance of Test 3 in the mini-BESTest, specifically standing on one leg, is a reliable indicator of whether an individual is blind or not. Most sighted individuals demonstrated an adequate balance when standing on one leg, whereas blind individuals exhibited a notable discrepancy in their performance.

Secondly, following the analysis of the evaluation test without the inclusion of IMU data, a series of methodologies were proposed for the treatment of this data in order to predict the three categories: (bad, mild, good) that Test 3 of the mini-BESTest was evaluated.

In addition, several AI model architectures were tested to treat time series data: CNN-1D, LSTM, GRU and CNN-LSTM (option 1 and 2). As a result, the hybrid model (CNN-LSTM option 2) presented the best accuracy and F1-score using multiclass classification. On the other hand, among feature extraction architectures: CNN and the first part of CNN-LSTM, it helps the models to learn quickly. However, models based on treating sequences spend more time to the predictions. For instance, LSTM and GRU.

Moreover, it is of great importance to consider how the data is presented to the AI model in order to be trained. Test 3 has the particularity that it is necessary to consider both legs separately in order to obtain the final punctuation, taking the worst leg evaluated. The most effective methodology for obtaining the prediction was methodology 2, which included the punctuation of each leg separately. The multiclass classification model achieved an accuracy of 80% and an F1-score of 61% when acceleration was used as the input data and a sliding window of 25 was employed, which is half the sample frequency.

Furthermore, the discussion of the optimal size of the sliding window and the most appropriate type of sensor data to utilize following the experiment revealed that with half the frequency of IMU acquisition (25 Hz), performance metrics can be obtained that are comparable to those obtained with the acquisition frequency (50 Hz). Additionally, a comparison of input time series utilizing raw acceleration yielded results that were similar to those obtained with quaternions, with the latter requiring more calculations.

Finally, the optimal number of sensors to register this type of movement was 6 considering the activity standing on one leg (Test 3).

Chapter 8. Future Lines

IMU vs. MOCAP for HAR

This work explores the applicability of DL methodologies with sliding windows to be used in HAR activities. The results obtained presented excellent accuracy in the identification of the tested models, even considering that two similar movements were used in the learning and testing steps. Moreover, the time needed to identify the movements was quite short, since all tested configuration presented values under 1 ms. These outcomes allow the use of these methodologies in HAR in real-time. Additionally, this study shows that accelerometer data can be efficiently used in the recognition of different human movements. This issue is particularly relevant, as it can be implemented in technologies used daily, such as the mobile phone, smart-watch, or any simple device developed using an accelerometer.

As limitations, a fixed frequency was used in the data acquisition process, therefore other results may be obtained if different frequencies are considered. Moreover, the present study considers only 3 activities, so the network might be restricted. Hence, future works may consider the analysis of a larger number of movements and also the analysis of non-pathological and pathological.

Future research on more complex HAR problems for which our results might be applicable, as might be the capability to distinguish between correct and wrong movements for a given person, or to monitor the evolution of the performance when repeating a given activity. Also, a test with other frequencies to obtain the optimal window size for different systems, for instance in kinetics where depth cameras or video cameras with human tracking are used, since these systems usually work with lower frequencies.

Applied Case in Blinds

Furthermore, this thesis represents a significant milestone in an extensive research project. The creation of a new database is based on a study of balance that includes participants who are both sighted and blind and may expand in the future to include those with low vision.

It is recommended that the database be expanded to include a greater range of population variability to obtain more samples of individuals with poor, medium, and good balance.

To ensure non-invasiveness and wearability, we propose a wireless device for data acquisition. Alternatively, video can also be used to acquire data.

It would be interesting to create a dataset that includes each balance test and adapts it for blind individuals, given the availability of more balance tests.

Additionally, in the future, it may be possible to evaluate other aspects related to AI methodology:

- Detecting the type of activity could automate the evaluation process.
- One aspect to consider is the potential regression in the relationship between the final score and the sequence of activities, although further investigation may be required.
- The final score is calculated by summing up the categorical evaluations. To account for temporal information, we can use 'features', although this approach has not yet been tested.

Chapter 9. Scientific Contribution

9.1 Published Articles

Title: Accuracy Comparison of CNN, LSTM, and Transformer for Activity Recognition Using IMU and Visual Markers

Authors: María Fernanda Trujillo-Guerrero, StadyN Román-Niemes, Milagros Jaén-Vargas, Alfonso Cadiz, Ricardo Fonseca, and José Javier Serrano-Olmedo.

Journal: IEEE Access.

DOI: [10.1109/ACCESS.2023.3318563](https://doi.org/10.1109/ACCESS.2023.3318563)

Date of submission: August 2023.

Data available at GitHub:

<https://github.com/StadyN/HAR-imu-photogrammetry>

Abstract: Human activity recognition (HAR) has applications ranging from security to healthcare. Typically, these systems are composed of data acquisition and activity recognition models. In this work, we compared the accuracy of two acquisition systems: Inertial Measurement Units (IMUs) vs Movement Analysis Systems (MAS). We trained models to recognize arm exercises using state-of-the-art deep learning architectures and compared their accuracy. MAS uses a camera array and reflective markers. IMU uses accelerometers, gyroscopes, and magnetometers. Sensors of both systems were attached to different locations of the upper limb. We captured and annotated 3 datasets, each one using both systems simultaneously. For activity recognition, we trained 8 architectures, each one with different operations and layers configurations. The best architectures were a combination of CNN, LSTM, and Transformer achieving test accuracy from 89% to 99% on average. We evaluated how feature selection reduced the sensors required. We found IMU and MAS data were able to distinguish correctly the arm exercises. CNN layers at the beginning produced better accuracy on challenging datasets. IMU had advantages over other acquisition systems for activity recognition. We analyzed the relations between models accuracy, signal waveforms, signals correlation, sampling rate, exercise duration, and window size. Finally, we proposed the use of a single IMU located at the wrist and a variable-size window extraction.

Title: Effects of Sliding Window Variation in the Performance of Acceleration-Based Human Activity Recognition using Deep Learning Models

Authors: Milagros Jaén-Vargas, Karla Miriam Reyes Leiva, Francisco Fernandes, Sérgio Barroso Gonçalves, Miguel Tavares Silva, Daniel Simões Lopes and José Javier Serrano Olmedo.

Journal: Peer J Computer Science.

DOI: [10.7717/peerj-cs.1052](https://doi.org/10.7717/peerj-cs.1052)

Date of submission: August 2022.

Data available at GitHub:

https://github.com/mjaenvargas/Sliding_Window_DL_IMU_MOCAP

Abstract: Deep learning (DL) models are very useful for human activity recognition (HAR); these methods present better accuracy for HAR when compared to traditional, among other advantages. DL learns from unlabeled data and extracts features from raw data, as for the case of time-series acceleration. Sliding windows is a feature extraction technique. When used for preprocessing time-series data, it provides an improvement in accuracy, latency, and cost of processing. The time and cost of preprocessing can be beneficial especially if the window size is small, but how small can this window be to keep good accuracy? The objective of this research was to analyze the performance of four DL models: a simple deep neural network (DNN); a convolutional neural network (CNN); a long short-term memory network (LSTM); and a hybrid model (CNN-LSTM), when varying the sliding window size using fixed overlapped windows to identify an optimal window size for HAR. We compare the effects in two acceleration sources: wearable inertial measurement unit sensors (IMU) and motion capture systems (MOCAP). Moreover, short sliding windows of sizes 5, 10, 15, 20, and 25 frames to long ones of sizes 50, 75, 100, and 200 frames were compared. The models were fed using raw acceleration data acquired in experimental conditions for three activities: walking, sit-to-stand, and squatting. Results show that the most optimal window is from 20–25 frames (0.20–0.25s) for both sources, providing an accuracy of 99,07% and F1-score of 87,08% in the (CNN-LSTM) using the wearable sensors data, and accuracy of 98,8% and F1-score of 82,80% using MOCAP data; similar accurate results were obtained with the LSTM model. There is almost no difference in accuracy in larger frames (100, 200). However, smaller windows present a decrease in the F1-score. In regard to inference time, data with a sliding window of 20

frames can be preprocessed around 4x (LSTM) and 2x (CNN-LSTM) times faster than data using 100 frames.

Title: A Proposal of a Motion Measurement System to Support Visually Impaired People in Rehabilitation Using Low-Cost Inertial Sensors

Authors: Karla Miriam Reyes Leiva, Milagros Jaén-Vargas, Miguel Ángel Cuba, Sergio Sánchez Lara and José Javier Serrano Olmedo

Journal: Entropy

DOI: [10.3390/e23070848](https://doi.org/10.3390/e23070848)

Date of submission: July 2021.

Data availability statement:

https://docs.google.com/spreadsheets/d/1-4NMnHSUrvO-NimwVJImX7G-dZibNwdqc_E2CO-AR00/edit#gid=1923287140

Abstract: The rehabilitation of a visually impaired person (VIP) is a systematic process where the person is provided with tools that allow them to deal with the impairment to achieve personal autonomy and independence, such as training for the use of the long cane as a tool for orientation and mobility (O&M). This process must be trained personally by specialists, leading to a limitation of human, technological and structural resources in some regions, especially those with economical narrow circumstances. A system to obtain information about the motion of the long cane and the leg using low-cost inertial sensors was developed to provide an overview of quantitative parameters such as sweeping coverage and gait analysis, that are currently visually analyzed during rehabilitation. The system was tested with 10 blindfolded volunteers in laboratory conditions following constant contact, two points touch, and three points touch travel techniques. The results indicate that the quantification system is reliable for measuring grip rotation, safety zone, sweeping amplitude and hand position using orientation angles with an accuracy of around 97.62%. However, a new method or an improvement of hardware must be developed to improve gait parameters' measurements, since the step length measurement presented a mean accuracy of 94.62%. The system requires further development to be used as an aid in the rehabilitation process of the VIP. Now, it is a simple and low-cost technological aid that has the potential to improve the current practice of O&M.

Title: Inertial Measurement Unit Sensors in Assistive Technologies for Visually Impaired People, a Review

Authors: Karla Miriam Reyes Leiva, Milagros Jaén-Vargas, Benito Codina and José Javier Serrano Olmedo

Journal: Sensors.

DOI: [10.3390/s21144767](https://doi.org/10.3390/s21144767)

Date of submission: July 2021.

Abstract: A diverse array of assistive technologies have been developed to help Visually Impaired People (VIP) face many basic daily autonomy challenges. Inertial measurement unit sensors, on the other hand, have been used for navigation, guidance, and localization but especially for full body motion tracking due to their low cost and miniaturization, which have allowed the estimation of kinematic parameters and biomechanical analysis for different field of applications. The aim of this work was to present a comprehensive approach of assistive technologies for VIP that include inertial sensors as input, producing results on the comprehension of technical characteristics of the inertial sensors, the methodologies applied, and their specific role in each developed system. The results show that there are just a few inertial sensor-based systems. However, these sensors provide essential information when combined with optical sensors and radio signals for navigation and special application fields. The discussion includes new avenues of research, missing elements, and usability analysis, since a limitation evidenced in the selected articles is the lack of user-centered designs. Finally, regarding application fields, it has been highlighted that a gap exists in the literature regarding aids for rehabilitation and biomechanical analysis of VIP. Most of the findings are focused on navigation and obstacle detection, and this should be considered for future applications.

9.2 Conference Articles

9.2.1 International Conference

Title: A Deep Learning Approach to Recognize Human Activity Using Inertial Sensors and Motion Capture Systems

Authors: M. Jaén-Vargas, K. Reyes Leiva, F. Fernandes, S.B. Gonçalves, M. Tavares Silva, D.S. Lopes, J. Serrano Olmedo

Conference proceedings: The 7th International Conference on Fuzzy Systems and Data Mining (FSDM).

DOI: [10.3233/FAIA210196](https://doi.org/10.3233/FAIA210196)

Date of publication: October 2021.

Abstract: Human Activity Recognition (HAR) plays an important role in behavior analysis, video surveillance, gestures recognition, gait analysis, and posture recognition. Given the recent progress of Artificial Intelligence (AI) applied to HAR, the inputs that are the data from wearable sensors can be treated as time-series from which movement events can be classified with high accuracy. In this study, a dataset of raw sensor data served as input to four different deep learning networks (DNN, CNN, LSTM, and CNN-LSTM). Differences in accuracy and learning time were then compared and evaluated for each model. An analysis of HAR was made based on an attempt to classify three activities: walking, sit-to-stand, and squatting. We also compared the performance of two different sensor data types: 3-axis linear acceleration measured from two inertial measurement units (IMUs) versus 3D acceleration of two retro-reflective markers from the high-end optoelectronic motion capture system (MOCAP). The dataset created from observations of ten subjects was preprocessed with labelling and sliding windows and then used as input to the four frameworks. The results indicate that, for HAR prediction, linear accelerations estimated using IMUs are as reliable as those measured using the MOCAP system. Also, the use of the hybrid CNN-LSTM framework for both methods resulted in higher accuracy (99%).

9.2.2 National Conference Articles

Title: Impact of Integrated Signals for doing HAR using Deep Learning Models.

Authors: M. Jaén-Vargas, J. García Martínez, K. Reyes Leiva, M. Trujillo-Guerrero¹, F. Fernandes, Barroso Gonçalves, M. Tavares Silva, D. Simões Lopes, J. Serrano Olmedo.

Conference proceedings: Congreso Anual de la Sociedad Española de Ingeniería Biomédica (CASEIB). Poster presentation.

Year of publication: 2023.

Abstract: Human Activity Recognition (HAR) is having a growing impact in creating new applications and is responsible for emerging new technologies. Also, the use of wearable sensors is an important key to exploring the human body's

behavior when performing activities. Hence, the use of these dispositive is less invasive and the person is more comfortable. In this study, a database that includes three activities is used. The activities were acquired from inertial measurement unit sensors (IMU) and motion capture systems (MOCAP). The main objective is differentiating the performance from four Deep Learning (DL) models: Deep Neural Network (DNN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and hybrid model Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM), when considering acceleration, velocity and position and evaluate if integrating the IMU acceleration to obtain velocity and position represent an increment in performance when it works as input to the DL models. Moreover, compared with the same type of data provided by the MOCAP system. Despite the acceleration data is cleaned when integrating, results show a minimal increase in accuracy for the integrated signals.

Title: Development of a Motion Measurement System of a Long Cane for Visually Impaired People in Rehabilitation

Authors: K. M. Reyes Leiva S. Sanchez Lara, M. Jaén-Vargas, J. J. Serrano Olmedo

Conference proceedings: Congreso Anual de la Sociedad Española de Ingeniería Biomédica (CASEIB). Oral presentation.

Year of publication: 2020.

Abstract: The rehabilitation of a blind person is a systematic process where the person is dotted with tools that allow them to deal with the impairment, including the correct use of the long cane for navigation in the Orientation and Mobility training. In this process, technology as inertial measurement sensors could be included to track the motion of the cane in order to evaluate the correct use. One sensor added to the cane can provide valuable information about the orientation, position, velocity, and trajectory of the tip. In this research, a system was developed by adding a BNO055 inertial sensor to the lower part of the long cane in order to analyze the output with the help of Arduino, Simulink, and MATLAB. A method was developed to obtain qualitative information about the movements of the long cane during the training of mobility and the reliability was tested. The tests were carried out with a real cane, in isolated situations and a controlled environment, corresponding to real techniques that will be trained during rehabilitation. The experimental results indicate that the parameters obtained in the orientation test and in the short displacement test presented a standard error

~1% in both cases and an accuracy of 98 and 97% respectively. However, for the sliding test for simulation of the diagonal technique, the difference in the value of the mean obtained with respect to the real value was 39%. Despite presenting reproducibility in tests with low standard errors, to obtain precise displacement or position value, a more complex census is required, or a new method should be developed for evaluation. The system requires further development in order to be used in the assistant program for the rehabilitation process.

Title: Photo Vector Extraction using Deep Learning Techniques for Cognitive Map Index Calculation.

Authors: M. Jaén-Vargas, M. Fernández Cerezo, K. Reyes Leiva, F. Ortiz-Gomez, A. Cobo, J. Serrano Olmedo.

Conference proceedings: Congreso Anual de la Sociedad Española de Ingeniería Biomédica (CASEIB). Poster presentation.

Year of publication: 2020.

Abstract: The main purpose of this project was to automate the process of acquisition of 3 vectors from images taken from the recreation of an experiment executed for impaired people. In this system a smartphone application was used for Point of Interest (POI) identification and where the scenario was previously virtualized. Thereby, once having the vectors the CMQ index was obtained in a more efficient and less time-consuming process. In order to automate the process, Deep Learning techniques were applied, principally, two supervised learning approaches: regression and classification. While classification helps to improve the model, the regression approach is closer to the expected result. However, neither of the two types of algorithms provides the desired results since the model presents a high error in the prediction, although in turn they show a clear capacity for improvement. Regarding the technologies used in the study, Python is the main language for coding besides Google Collab where compiling models in the cloud.

Title: Indoor Guide System Developed for Visually Impaired People.

Authors: J. Arranz Sanz, M. Jaén Vargas, J. Serrano Olmedo.

Conference proceedings: Congreso Anual de la Sociedad Española de Ingeniería Biomédica (CASEIB). Poster presentation

Year of publication: 2019.

Abstract: This project is aimed to cover the visually impaired people need regarding their “first visit” to a new environment and increase their autonomy. Nowadays, the idea of a visually impaired person going on his own to a new place is unfeasible due to self-security lack. The main purpose of this project is to develop a guidance system for visually impaired people, so they familiarize with a new environment relying only on technology without the need of any external support (besides the blind cane). The objective is to guide the user by the means of previously recorded “waypoints” creating a recognizable path by computational means in order to guide the user accordingly. Regarding technologies used in the project, Unity will be the base SDK to develop an Augmented Reality solution. The tests will be conducted on a smartphone platform with accelerometer, gyroscope, and camera.

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Appendix

Appendix A.

In the next page is displayed the information issued by the Ethics Committee of the Universidad Politécnica de Madrid to the project named: "Analysis of body posture in visually impaired and sighted people", with reference ADPCEPCDDVY-JJSO-DATOS-20230329, whose principal investigator is José Javier Serrano Olmedo, from Assistive Technologies for Life.

This was signed on April 10, 2023.

Additionally, the informed consent form is displayed, where the study was explained to each participant, as well as the data protection policy.



UNIVERSIDAD
POLITÉCNICA
DE MADRID

**INFORME QUE EMITE EL COMITÉ DE ÉTICA
DE LA UNIVERSIDAD POLITÉCNICA DE MADRID**

A petición de la Vicerrectora de Investigación, Innovación y Doctorado de la Universidad Politécnica de Madrid,

D^a Asunción Gómez Pérez, de un dictamen sobre los aspectos éticos del

Proyecto **“Análisis de postura corporal en personas con discapacidad visual y con visión”**, con referencia ADPCEPCDVY-JJSO-DATOS-20230329, cuyo investigador principal es José Javier Serrano Olmedo, de Tecnologías de Apoyo a la Vida.

El Comité emite el siguiente informe:

El solicitante declara conocer los principios éticos y las normas legales que rigen las actividades de investigación y se compromete a respetar estos principios y normas en el desarrollo del estudio propuesto. Igualmente, se compromete a no modificar los protocolos de investigación y a solicitar una nueva autorización en caso de modificación.

El solicitante declara conocer la legislación relativa a la protección de datos y se compromete a respetar la confidencialidad de los datos personales de este estudio, así como a hacer explícito este compromiso ante las personas que participan en el proyecto.

El solicitante declara conocer, en particular, el Reglamento (UE) 2016/679 del Parlamento Europeo y del Consejo, de 27 de abril de 2016, relativo a la protección de las personas físicas en lo que respecta al tratamiento de datos personales y a la libre circulación de estos datos y por el que se deroga la Directiva 95/46/CE (Reglamento general de protección de datos), y se compromete a cumplirlo.

Igualmente, se compromete a no modificar los protocolos de investigación y a solicitar una nueva autorización en caso de modificación.

Por lo tanto, no hay inconveniente en **informar favorablemente la propuesta**, recomendando el efectivo cumplimiento de los compromisos declarados.

Y para que así conste, firmo el presente informe en Madrid.

La Presidenta del Comité

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ASUNCION DE
MARIA GOMEZ
(R: Q2818015F)
Firmado digitalmente
por 08821929A
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GOMEZ (R: Q2818015F)
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Asunción Gómez Pérez

El Secretario del Comité

DUEÑAS LOPEZ JUAN CARLOS - DNI ***0290** with a
certificate issued by/con un certificado emitido
por AC Sector Público

Juan Carlos Dueñas López

UNIVERSIDAD POLITÉCNICA DE MADRID **Vicerrectorado de Investigación, Innovación y Doctorado**
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Appendix A. Ethics Committee information.



CARTA DE CONSENTIMIENTO INFORMADO

Dirigido a: Participantes voluntarios con discapacidad visual y con visión

Nombre del Estudio: Análisis de postura corporal en personas con discapacidad visual y visión.

Entidades Promotoras: Universidad Politécnica de Madrid (UPM).

Nombre del Investigador Principal: Prof. Dr. José Javier Serrano Olmedo.

Estimado(a) Señor/Señora:

Usted ha sido invitado a participar en el presente proyecto de investigación, el cual es desarrollado por el Laboratorio de Bioinstrumentación y Nanomedicina (LBN) del Centro de Tecnología Biomédica (CTB) de la Universidad Politécnica de Madrid (UPM).

Si Usted decide participar en el estudio, es importante que lea la siguiente información (carta consentimiento informado) y, si está de acuerdo con los términos presentados, firme el documento en el lugar indicado.

Su participación es voluntaria y puede retirarse en cualquier momento sin penalización o consecuencia. Además, siéntase libre de preguntar cualquier asunto que no le quede claro.

Se le suministrará una copia de este consentimiento una vez haya sido firmado.

- a. **Objetivos y Descripción del Estudio:** Este estudio tiene como principal objetivo registrar el movimiento de su cuerpo de acuerdo con las actividades incluidas en un test de evaluación del equilibrio corporal (mBEST test). De esta manera, crear una base de datos, que se usará para entrenar programas de ordenador de inteligencia artificial (IA) y con ello estudiar la postura corporal en personas con discapacidad visual.
La adquisición de dato se hará con unos sensores de muy poco peso que se pondrán sujetos al cuerpo sobre la ropa sin dañarla, sobre brazos, piernas, tronco y con unas gafas. La prueba está dividida en cuatro partes a considerar y nos permitirá evaluar una parte anticipatoria, el control postural reactivo, la orientación sensorial, así como la marcha dinámica del participante.
- b. **Elegibilidad:** Le pedimos participar en este estudio porque usted forma parte del grupo de personas con discapacidad visual que posee movilidad y autonomía.
- c. **Localidad:** Para facilitar el desplazamiento y generar una base de datos que contenga valores en ambientes naturales y conocidos por el voluntario, nos desplazaremos a su domicilio ó, si usted lo prefiere puede acudir al laboratorio.
- d. **Duración esperada de su participación:** El estudio tendrá una duración estimada de una hora y media, pero podrá demorar menos de ese tiempo.
- e. **Procedimiento:** La evaluación consistirá en la recolección y análisis experimental de actividades que conforman el mBEST test mencionado arriba.
Para esto, se le colocarán en su cuerpo 12 sensores pequeños y un cinturón que tendrá un botón para empezar a grabar mientras se haga la actividad.
- f. **Beneficios de la participación:** La participación en este estudio es enteramente voluntaria. Por ende, no hay beneficios directos asociados a la participación en este estudio, ni otros tipos de incentivos que pudiesen alterar la calidad de la muestra utilizada para el desarrollo del mismo.



- g. **Confidencialidad:** Toda la información recaudada en el estudio será de carácter estrictamente confidencial, será utilizada únicamente por el equipo de investigación del proyecto y no estará disponible para ningún otro propósito. Si los resultados de este estudio fuesen publicados, será estrictamente con fines científicos, pero se presentarán de tal manera que usted no podrá ser identificado(a).
- h. **Aviso de Privacidad:** El investigador principal de este estudio, Dr. José Javier Serrano, es responsable del tratamiento y resguardo de los datos personales que nos proporcione, los cuales serán protegidos conforme a lo dispuesto por la **Ley General de Protección de Datos Personales**. Los datos personales que le solicitaremos serán utilizados exclusivamente para las finalidades expuestas en este documento. Usted puede solicitar la corrección de sus datos o que sus datos se eliminen de nuestras bases o retirar su consentimiento para su uso. En cualquiera de estos casos le pedimos dirigirse al investigador responsable del proyecto a la siguiente dirección de correo josejavier.serrano@ctb.upm.es

INFORMACIÓN BÁSICA SOBRE PROTECCIÓN DE DATOS	
Responsable	Universidad Politécnica de Madrid (D. José Javier Serrano Olmedo, de Tecnologías de Apoyo a la Vida).
Finalidad	Gestionar su participación, como persona voluntaria, en el proyecto “Análisis de postura corporal en personas con discapacidad visual y con visión”, incluyendo entre los datos personales a tratar la grabación de su voz e imagen durante las sesiones correspondientes.
Derechos	Acceder, rectificar, y suprimir los datos, así como otros derechos, en los términos y con las limitaciones que se indican en la información adicional.
Información adicional	Puede consultar la información adicional y detallada sobre Protección de Datos en el documento adjunto.

- i. Para cualquier información de este proyecto, recurrir al comité de ética cuya dirección de correo es la siguiente: secretaria.adjunto.vinvestigacion@upm.es

Información de contacto: Para cualquier pregunta, comentario o preocupación con respecto al estudio, por favor comuníquese con el grupo de investigación responsable del proyecto:

- Dña. Milagros Jaén Vargas - Investigadora predoctoral. Disponibilidad: 11-20 horas. Número de teléfono: 910 67 92 50 ext.: 79269 email: milagros.jaen@ctb.upm.es.
- Don Shiyang Li – Investigador predoctoral. Disponibilidad: 11-20 horas. Número de teléfono 910 67 92 50 ext.: 79269 email: shiyangli@ctb.upm.es.
- Dña. Karla Miriam Reyes Leiva - Investigadora predoctoral. Disponibilidad: 12-20 horas. Número de teléfono 910 67 92 50 ext.: 79269 email: karla.reyes@ctb.upm.es.

**Autorización para participar en el ensayo**

1. He leído, o me lo leyeron, y entiendo los objetivos del estudio, así como qué esperar con respecto a mi participación. Tuve la oportunidad de hacer preguntas, si era necesario, y recoger las respectivas respuestas.
2. Entiendo que la participación en este estudio es voluntaria y que puedo retirarme en cualquier momento, sin dar ninguna explicación. Si esto sucede, no seré objeto de ninguna penalización y los datos relacionados con mi experiencia serán eliminados y destruidos.
3. Declaro que no estoy dentro de los criterios de exclusión.
4. Autorizo la grabación de audio y video durante la sesión.
5. Autorizo el tratamiento de datos audiovisuales con fines de análisis, investigación y difusión de resultados en publicaciones científicas o congresos en áreas relacionadas con los temas del proyecto.
6. Entiendo que los datos recopilados en este estudio se utilizarán como se menciona previamente.

Por lo tanto, declaro que acepto voluntariamente participar en este estudio. También les informo que fue entregado a mí o a mi representante una copia de este documento debidamente firmado por un de los responsables del estudio.

Nombre del Participante: _____

Firma: _____

Fecha: _____

Nombre del Representante Legal (si corresponde) *: _____

*El tutor debe aceptar el consentimiento en caso de que el participante sea menor de edad

Firma: _____

Fecha: _____

Nombre del investigador: _____

Firma: _____

Fecha: _____



INFORMACIÓN ADICIONAL SOBRE PROTECCIÓN DE DATOS

- ¿Quién es el responsable del tratamiento de sus datos?
 - Identidad: Universidad Politécnica de Madrid (D. José Javier Serrano Olmedo, de Tecnologías de Apoyo a la Vida).
 - Dirección Postal: Universidad Politécnica de Madrid, Parque Científico y Tecnológico, Campus de Montegancedo, M40 km 38, 28223 Pozuelo de Alarcón.
 - Teléfono/ correo electrónico: 910 67 92 50, josejavier.serrano@ctb.upm.es
- Contacto Delegado Protección de Datos: proteccion.datos@upm.es
- ¿Con qué finalidad se tratan sus datos personales?
 - Sus datos personales, incluyendo la grabación de su voz e imagen durante las sesiones correspondientes, se tratan con la finalidad de gestionar su participación como persona voluntaria en el proyecto “Análisis de postura corporal en personas con discapacidad visual y con visión”.
- ¿Por cuánto tiempo conservaremos sus datos?
 - Los datos personales se conservarán durante el tiempo necesario para cumplir con la finalidad para la que se recabaron y para determinar las posibles responsabilidades que se pudieran derivar de dicha finalidad y del tratamiento de los datos, además de los periodos establecidos en la normativa de archivos y documentación.
- ¿Cuál es la legitimación para el tratamiento de sus datos?
 - Las bases legales que legitiman el tratamiento son las recogidas en el Reglamento (UE) 2016/679: Artículo 6.1.a) el interesado dio su consentimiento para el tratamiento de sus datos personales para uno o varios fines específicos.
 - Artículo 6.1.e) “Tratamiento necesario para el cumplimiento de una misión de interés público”, consistente en la investigación que se realiza
- ¿Tiene Ud. la obligación de facilitar estos datos personales y cuáles son las consecuencias de no hacerlo?
 - Los datos solicitados son los estrictamente necesarios para llevar a cabo el estudio, motivo por el que no será posible su participación si no los facilita, debido al carácter totalmente voluntario de este proyecto de investigación.
- ¿A qué destinatarios se comunicarán sus datos?
 - No se prevé la comunicación de sus datos a terceros.
- ¿Cuáles son sus derechos en relación con los datos facilitados?
 - En relación a los datos facilitados tiene derecho a acceder, rectificar, solicitar la cancelación y supresión y a oponerse o a limitar el tratamiento de los mismos, en los términos establecidos legalmente.
 - Puede obtener más información sobre el ejercicio de estos derechos contactando con el Delegado de Protección de Datos de la UPM.
 - Asimismo, y en el supuesto de que no obtenga satisfacción en el ejercicio de sus derechos, podrá presentar una reclamación ante la Agencia Española de Protección de Datos: <https://www.aepd.es/es>

Appendix B.

This section presents the Spanish adaptation of the mini-BESTest, which includes all the activities and their respective indications within the test. Additionally, it outlines the sub-punctuation for each area or section of the test.

Mini-BESTest: Test de evaluación de los sistemas de equilibrio

Nombre / código del sujeto	Fecha	Evaluador/a
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ANTICIPATORIO

SUBPUNTUACIÓN: /6

1. DE SENTADO A DE PIE

Instrucción: "Cruce los brazos sobre el pecho". Intente no usar las manos salvo que lo necesite. No deje que sus piernas se apoyen contra el borde de la silla cuando esté de pie. Por favor, ahora póngase de pie.

- ☐ (2) Normal: Se pone de pie sin usar las manos y se estabiliza independientemente.
☐ (1) Moderado: Se pone de pie USANDO sus manos en el primer intento.
☐ (0) Grave: Incapaz de ponerse de pie desde la silla sin ayuda de un asistente O precisa de varios intentos con la ayuda de sus manos.

2. PONERSE DE PUNTILLAS

Instrucción: "Coloque sus pies separados a la anchura de los hombros. Coloque sus manos en sus caderas. Intente ponerse de puntillas tan alto como pueda. Contaré en voz alta hasta 3. Intente mantenerse en esa posición al menos 3 segundos. Mire al frente. Póngase de puntillas...ahora."

- ☐ (2) Normal: Estable durante 3 segundos con la altura máxima.
☐ (1) Moderado: Levanta los talones, pero no con el rango máximo (más pequeño que cuando se sujeta con las manos) O notable inestabilidad durante 3 s.
☐ (0) Grave: < 3 s.

3. APOYO MONOPODAL

Instrucción: "Mire al frente. Mantenga las manos en sus caderas. Póngase a la pata coja (levantando su otra pierna hacia atrás). No toque con su pierna elevada la pierna de apoyo. Permanezca sobre la pierna tanto como pueda. Mire al frente. Levántela ahora."

Izda: Tpo en s Prueba 1:

Prueba 2:

Dcha: Tpo en s Prueba 1:

Prueba 2:

- ☐ (2) Normal: 10 s
☐ (1) Moderado: 5 s
☐ (0) Grave: Incapaz

- ☐ (2) Normal: 10 s
☐ (1) Moderado: 5 s
☐ (0) Grave: Incapaz

Para registrar cada lado por separado use la prueba de mayor duración. Para calcular la subpuntuación y la puntuación total use el lado [izdo o dcho] con la puntuación numérica más baja [el lado peor].

CONTROL POSTURAL REACTIVO

SUBPUNTUACIÓN: /6

4. CORRECCIÓN COMPENSATORIA CON UN PASO HACIA DELANTE

Instrucción: "Coloque sus pies separados a la anchura de los hombros, brazos a los lados. Inclínese hacia delante apoyándose en mis manos más allá de sus límites anteriores. Cuando lo suelte, haga lo que sea necesario, incluido dar un paso, para evitar una caída."

- ☐ (2) Normal: Recupera de forma independiente con un solo y gran paso (el segundo paso de realineación es permitido).
☐ (1) Moderado: usa más de un paso para recuperar el equilibrio.
☐ (0) Grave: sin paso O podría caer si no fuera cogido O cae de manera espontánea.

5. CORRECCIÓN COMPENSATORIA CON UN PASO HACIA ATRÁS

Instrucción: "Coloque sus pies separados a la anchura de los hombros, brazos a los lados. Inclínese hacia detrás contra mis manos, más allá de sus límites posteriores. Cuando lo suelte, haga lo que sea necesario, incluido dar un paso, para evitar una caída."

- ☐ (2) Normal: Recupera de forma independiente con un solo y gran paso (el segundo paso de realineación es permitido).
☐ (1) Moderado: usa más de un paso para recuperar el equilibrio.
☐ (0) Grave: sin paso O podría caer si no fuera cogido O cae de manera espontánea.

6. CORRECCIÓN COMPENSATORIA CON UN PASO LATERAL

Instrucción: "Póngase de pie, con los pies juntos, brazos a los lados. Inclínese hacia mi mano más allá de sus límites laterales. Cuando lo suelte, haga lo que sea necesario, incluido dar un paso, para evitar una caída."

Izquierda

Derecha

- ☐ (2) Normal: recupera de forma independiente con un paso (cruza-
do o lateral es correcto).
☐ (1) Moderado: varios pasos para recuperar el equilibrio.
☐ (0) Grave: caída o no puede dar el paso.

- ☐ (2) Normal: recupera de forma independiente con un paso (cruza-
do o lateral es correcto).
☐ (1) Moderado: varios pasos para recuperar el equilibrio.
☐ (0) Grave: caída o no puede dar el paso.

Use el lado con la puntuación más baja para calcular la subpuntuación y la puntuación total.

Appendix B. mini-BESTest form.

ORIENTACIÓN SENSORIAL

SUBPUNTUACIÓN: /6

7. DE PIE (PIES JUNTOS); OJOS ABIERTOS (SI HAY RESTO VISUAL), SUPERFICIE FIRME

Instrucción: "Coloque sus manos en sus caderas. Coloque sus pies juntos hasta que casi se toquen. Mire al frente. Permanezca tan estable como sea posible hasta que yo diga que pare."

Tiempo en segundos:

- ☐ (2) Normal: 15 s.
☐ (1) Moderado: < 15s.
☐ (0) Grave: incapaz.

8. DE PIE (PIES JUNTOS); OJOS CERRADOS, SUPERFICIE DE GOMA ESPUMA

Instrucción: "Póngase en la gomaespuma. Coloque sus manos en las caderas. Coloque sus pies tan juntos que casi se toquen. Permanezca tan estable como sea posible, hasta que le diga que pare. Comenzaré a cronometrar cuando cierre sus ojos"

Tiempo en segundos:

- ☐ (2) Normal: 15 s.
☐ (1) Moderado: < 15 s.
☐ (0) Grave: incapaz.

9. INCLINADO; OJOS CERRADOS

Instrucción: "Sitúese en la rampa inclinada. Coloque los dedos de sus pies en la parte más elevada de la rampa. Coloque sus pies separados a la anchura de los hombros y sus brazos caídos a ambos lados del cuerpo. Comenzaré a cronometrar cuando cierre sus ojos"

Tiempo en segundos:

- ☐ (2) Normal: Bipedestación independiente 15 s y se alinea con la gravedad.
☐ (1) Moderado: Bipedestación independiente <15 s O se alinea con la superficie.
☐ (0) Grave: incapaz.

MARCHA DINÁMICA

SUBPUNTUACIÓN: /10

10. CAMBIO EN LA VELOCIDAD DE MARCHA

Instrucción: "Comience a caminar a su velocidad normal hacia mi voz. Cuando le diga "más rápido", camine tan rápido como pueda. Cuando le diga "lento", camine muy lentamente."

- ☐ (2) Normal: Cambios significativos en la velocidad de marcha sin desequilibrio.
☐ (1) Moderado: Incapaz de cambiar la velocidad de marcha o signos de desequilibrio.
☐ (0) Grave: Incapaz de realizar cambios significativos en la velocidad de marcha Y signos de desequilibrio.

11. CAMINAR CON GIROS DE CABEZA HORIZONTAL

Instrucción: "Comience caminando a su velocidad habitual hacia mi voz. Cuando le diga "derecha", gire su cabeza y mire hacia la derecha. Cuando le diga "izquierda", gire su cabeza y mire hacia la izquierda. Intente mantenerse caminando en línea recta".

- ☐ (2) Normal: realiza los giros de cabeza sin cambios en la velocidad de marcha y con buen equilibrio.
☐ (1) Moderado: realiza giros de cabeza con disminución de la velocidad de marcha.
☐ (0) Grave: realiza giros de cabeza con desequilibrio.

12. CAMINAR CON GIROS DE PIVOTE

Instrucción: "Comience caminando a su velocidad habitual hacia mi voz. Cuando le diga "gire y pare", dé la vuelta tan rápido como pueda y pare. Después del giro sus pies deben estar próximos."

- ☐ (2) Normal: gira con los pies próximos RÁPIDO (< 5 pasos) con buen equilibrio.
☐ (1) Moderado: Gira con los pies próximos ESPACIO (>5 pasos) con buen equilibrio.
☐ (0) Grave: No puede girar con los pies próximos a ninguna velocidad sin desequilibrio.

13. PASO POR ENCIMA DE OBSTÁCULOS

Instrucción: "Comience caminando a su velocidad habitual hacia mi voz. Cuando le avise de la presencia de la caja, pase por encima de ella, no alrededor y siga caminando".

- ☐ (2) Normal: Capaz de pasar por encima de la caja con cambio mínimo en la velocidad de marcha y con buen equilibrio.
☐ (1) Moderado: Pasos por encima de la caja, pero la toca O lo hace con prudencia enlenteciendo la marcha.
☐ (0) Grave: Incapaz de pasar por encima de la caja O pasos alrededor de la caja.

14. TEST UP & GO (TUG) (en español: "LEVANTARSE E IR") CRONOMETRADO CON DOBLE TAREA (MARCHA: 3 METROS)

Instrucción TUG: "Cuando le diga "vaya", levántese de la silla, camine a su velocidad normal hacia mi voz. Cuando le avise, dé la vuelta y siéntese en la silla".

Instrucción TUG con doble tarea: "Cuenta hacia atrás de 3 en 3 comenzando en Cuando le diga "vaya", levántese de la silla, camine a su velocidad normal hacia mi voz. Cuando le avise, dé la vuelta y siéntese en la silla. Continúe contando hacia atrás todo el tiempo."

TUG: segundos

TUG doble tarea: segundos

- ☐ (2) Normal: Sin cambios reseñables en sentarse, ponerse de pie o caminar mientras cuenta hacia atrás comparado con el TUG sin doble tarea.
☐ (1) Moderado: La tarea dual afecta al contar O al caminar (>20%) comparado con el TUG sin doble tarea.
☐ (0) Grave: Para de contar mientras camina O para de caminar mientras cuenta.

Quando puntúe el ítem 14, si la velocidad del sujeto se enlentece más del 10% entre el TUG sin y con tarea dual, la puntuación debería disminuir en un punto.

PUNTUACIÓN TOTAL: /28

Appendix C.

This section contains the instructions for the Mini-BESTest, which are used to evaluate each activity on the test, each area, and the total score.

Instrucciones para el Mini-BESTest

Condiciones del sujeto: el sujeto debería ser valorado con zapatos planos, o sin zapatos ni calcetines.

Familiarización: antes de empezar cada ejercicio, el evaluador deberá asegurarse de que el sujeto con discapacidad visual conoce el equipamiento que se va a utilizar y entiende las instrucciones. Para ello se le ofrecerán y se le pedirá que las repita. No es conveniente realizar intentos de prueba, pues ello podría suponer sobre-aprendizaje de la tarea.

Equipamiento: Goma espuma Temper® (también llamada T-foam™ de 10 cm de grosor, densidad media (T41, clasificación de firmeza), silla sin reposabrazos o ruedas, rampa inclinada, cronómetro, una caja (de 23 cm altura) y una marca con cinta adhesiva a 3 metros de distancia de la silla, pegada en el suelo, de color amarillo o de alto contraste para las personas con baja visión.

Puntuación: El test tiene una puntuación máxima de **28 puntos para 14 ítems**, valorados cada uno de ellos de 0 a 2. "0" indica el nivel de función más bajo y "2" el nivel de función más alto.

Si un sujeto necesita asistencia para un ítem, puntúe ese ítem una categoría más baja. Si un sujeto requiere asistencia física para realizar el ítem, puntúe "0" para ese ítem.

Para el ítem 3 (de pie en una pierna) e ítem 6 (paso compensatorio-lateral) sólo se incluye la puntuación para un lado (la peor puntuación). Para el ítem 3 (de pie en una pierna) seleccione el mejor tiempo de los dos registros (para un lado) para la puntuación.

Para el ítem 14 (Test Up & Go cronometrado con doble tarea) si la persona camina lentamente más de un 10% entre el TUG sin y con doble tarea, entonces la puntuación debe disminuir en un punto.

1.SENTADO A DE PIE	Anote el inicio del movimiento y el uso de las manos del sujeto en la silla, los muslos o el empuje de los brazos hacia delante.
2.PONERSE DE PUNTILLAS	Permita al sujeto cuatro intentos. Puntúe el mejor de ellos. (Si sospecha que el sujeto consigue menos que la máxima altura, pídale alzarse mientras coge las manos del examinador). Asegúrese de que el sujeto mira a un objetivo fijo situado a 1 - 4 m por delante.
3.MANTENERSE EN UNA PIERNA	Permita al sujeto cuatro intentos y registre los tiempos. Registre el número de segundos que el sujeto puede sostenerse, hasta un máximo de 20 s. Pare el tiempo cuando el sujeto mueva las manos de sus caderas o ponga un pie abajo. Asegúrese de que el sujeto mira a un objetivo fijo situado a 1 - 4 m por delante. Repita del otro lado.
4.CORRECCIÓN COMPENSATORIA CON UN PASO-HACIA DELANTE	Sitúese delante del paciente con una mano en cada hombro y pídale inclinarse hacia delante. (Asegúrese de que haya espacio libre para dar un paso). Solicite al sujeto que se incline hasta que sus hombros y caderas estén frente a los dedos de los pies. Después de que sienta el peso del sujeto en sus manos, quite su apoyo. El test debe producir un paso. NOTA: esté preparado para coger al sujeto.
5.CORRECCIÓN COMPENSATORIA CON UN PASO-HACIA ATRÁS	Sitúese por detrás del paciente con una mano en cada escápula y pídale inclinarse hacia atrás (Asegúrese de que hay espacio libre para dar un paso atrás.) Pida al paciente que se incline hasta que sus hombros y caderas estén por detrás de sus talones. Después de que sienta el peso del sujeto en sus manos, quite su apoyo. El test debe producir un paso. NOTA: esté preparado para coger al sujeto.
6.CORRECCIÓN COMPENSATORIA CON UN PASO-LATERAL	Sitúese de lado al sujeto, coloque sus manos en la hemipelvis homolateral del sujeto. Pídale que se incline hasta que la línea media de la pelvis esté por encima del pie dcho (o izdo) y después quite bruscamente su apoyo. NOTA: esté preparado para coger al sujeto.
7.DE PIE (PIES JUNTOS), OJOS ABIERTOS, SUPERFICIE FIRME	Registre el tiempo que el sujeto es capaz de estar de pie con los pies juntos hasta un máximo de 30 segundos. Asegúrese de que el sujeto mira a un objetivo fijo situado a 1 - 4 m por delante. Hacerlo cuatro veces.
8.DE PIE (PIES JUNTOS), OJOS CERRADOS, SUPERFICIE GOMAESPUMA	Use una gomaespuma de densidad media tipo Tempur® de 10 cm de grosor. Asista al sujeto para colocarse sobre ella. Registre el tiempo que el sujeto ha sido capaz de estar en esa condición hasta un máximo de 15 segundos. Entre los dos intentos, el sujeto se coloca fuera de la gomaespuma. Dé la vuelta a la gomaespuma entre registros para que el material recupere su forma original.
9.INCLINADO OJOS CERRADOS	Ayude al sujeto en la rampa. Una vez que haya cerrado los ojos (cuando sea necesario), comience a contar el tiempo y regístrelo. Anote si hay una oscilación excesiva. Hacerlo cuatro veces.
10.CAMBIOS EN LA VELOCIDAD	Permita al paciente dar entre 3 y 5 pasos a una velocidad normal y después diga "rápido". Después de 3-5 pasos rápidos, diga "despacio". Permita de 3 a 5 pasos antes de que el sujeto pare de caminar. Si el sujeto no puede verle delante de usted, guíele con la voz.
11. CAMINAR CON GIROS DE CABLEZA - HORIZONTAL	Permita al sujeto alcanzar su velocidad normal y dé las órdenes "dcha, izda" cada 3-5 pasos. Registre si ve algún problema en cualquier dirección. Si el sujeto tiene limitaciones cervicales, permita movimientos combinados de cabeza y tronco.
12.CAMINAR CON GIROS DE PIVOTE	Muestre un giro de pivote. Una vez que el sujeto camine a velocidad normal, diga "gire y pare." Cuente el número de pasos para "girar" hasta que el sujeto esté estable. El desequilibrio puede evidenciarse por una bipedestación con una base amplia, pasos extra o movimiento del tronco.
13. PASO POR ENCIMA DE OBSTÁCULOS	Coloque dos cajas de zapatos encintadas juntas (de 23 cm de altura cada una de ellas) a 3 metros de donde el sujeto comenzará a caminar.
14. TEST UP & GO CRONOMETRADO CON DOBLE TAREA	Use el TUG cronometrado para determinar los efectos de la tarea dual. El sujeto debe caminar una distancia de 3 metros. TUG: El sujeto ha de estar sentado con su espalda en contacto con el respaldo. Se le cronometrarán desde el momento en el que diga "vaya" hasta que vuelva a sentarse. Puntúe la tarea dual que afecta al contar o al caminar si la velocidad de marcha se ententece (>50%) con respecto al TUG y /o nuevos signos de desequilibrio.

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En la traducción y adaptación han participado: Domínguez-Oliván, P. Serrano-Del-Río, P. Fernández-Simon, F. Fisioterapeutas del Hospital Universitario Miguel Servet de Zaragoza (España). Bengoetxea, A. Fisioterapeuta. Université Libre de Bruxelles. Bolea-Moll, D. Traductor e intérprete. Traducción aprobada por F. Horak en 2017.

Appendix C. mini-BESTest – evaluation instructions.

Appendix D.

In this part all the plots where ML model training is shown.

Appendix D. Performance metrics in K-means.

Features	Wcss	Silhouette e	Davies_b ouldin	Calinski_h arabasz	Pearson
['Test 3']	[29.000, 4.843,	[0, 0.333,	[0, 1.418,	[0, 11.786,	[nan,
	3.081e-31,	0.280,	2.478,	7.020,	0.809,
	3.081e-31,	0.280,	2.478,	7.020,	0.738,
	3.081e-31,	0.280,	2.478,	7.020,	0.738,
	3.081e-31,	0.280,	2.478,	7.020,	0.738,
	3.081e-31,	0.280,	2.478,	7.020,	0.738,
	3.081e-31,	0.280,	2.478,	7.020,	0.738,
	8.628e-32]	0.280]	2.478]	7.020]	0.738]
['Test 3', 'Gender']	[36.034,	[0, 0.333,	[0, 1.418,	[0, 11.786,	[nan,
	11.525, 6.678,	0.280,	2.478,	7.020,	0.809,
	2.178, 0.750,	0.130,	2.188,	5.815,	0.758,
	9.183e-31,	0.188,	1.832,	6.825,	0.252,
	9.275e-31,	0.182,	1.581,	6.448,	0.285,
	2.730e-30,	0.182,	1.581,	6.448,	0.358,
	13.064]	0.182]	1.581]	6.448]	0.358,
	0.019,				0.294]
['Test 3', 'Age', 'Gender']	[65.034,	[0, 0.384,	[0, 1.317,	[0, 13.892,	[nan,
	25.197,	0.296,	1.567,	7.596,	0.751,
	19.560,	0.176,	1.475,	7.222,	0.748,
	14.886,	0.163,	1.938,	5.986,	0.040,
	10.984, 7.303,	0.118,	1.920,	4.934,	0.289,
	5.834, 4.167,	0.085,	1.712,	4.282,	0.179,
	2.972]	0.197,	1.443,	5.816,	0.071,
	0.106]	1.401]	5.089]	0.524,	0.256]
['Test 3', 'Age', 'Gender', 'Practice sports']	[68.483,	[0, 0.384,	[0, 1.317,	[0, 13.892,	[nan,
	28.244,	0.316,	1.847,	8.372,	0.7509,
	23.112,	0.183,	1.575,	8.273,	0.749,
	18.271,	0.050,	2.138,	5.173,	0.206,
	14.032,	0.118,	1.920,	4.934,	0.364,
	10.044, 8.305,	0.113,	1.686,	5.012,	0.011,
	6.434, 5.568]	0.123,	1.470,	4.732,	0.255,
	0.079]	1.362]	5.463]	0.652,	0.268]
['Test 3', 'Age', 'Height (m)', 'Gender', 'Practice sports']	[97.483,	[0, 0.384,	[0, 1.317,	[0, 13.892,	[nan,
	57.007,	0.230,	1.186,	12.4064,	0.751, -
	37.345,	0.199,	1.394,	9.939,	0.201, -
	30.914,	0.222,	1.274,	9.011,	0.221,
	22.389,	0.212,	1.674,	6.779,	0.045,
	19.357,	0.133,	1.714,	6.881,	0.682,

	16.494, 14.753, 12.367]	0.255, 0.101]	1.050, 1.484]	11.057, 6.484]	0.088, 0.420, 0.122]
['Test 3', 'Test 11', 'Age', 'Height (m)', 'Gender', 'Practice sports']	[126.483, 69.478, 48.750, 38.187, 29.212, 22.202, 18.524, 15.537, 12.873]	[0, 0.4312, 0.230, 0.199, 0.234, 0.221, 0.239, 0.210, 0.179]	[0, 1.135, 1.186, 1.394, 1.236, 1.196, 1.031, 1.194, 1.036]	[0, 17.544, 12.406, 9.939, 9.029, 7.772, 8.818, 7.831, 10.442]	[nan, 0.639, - 0.201, - 0.029, - 0.459, 0.738, 0.286, - 0.258, - 0.016]
	[155.483, 95.760, 67.806, 47.078, 35.934, 27.548, 20.814, 17.372, 14.394]	[0, 0.432, 0.417, 0.243, 0.249, 0.272, 0.258, 0.241, 0.235]	[0, 1.134, 0.847, 0.972, 1.049, 1.019, 1.001, 0.830, 0.996]	[0, 17.544, 14.808, 14.006, 14.038, 12.710, 12.253, 13.183, 12.779]	[nan, 0.639, 0.604, 0.262, 0.174, - 0.070, 0.332, 0.165, - 0.026]
	[184.483, 104.907, 76.865, 55.438, 43.319, 34.437, 27.205, 21.886, 16.388]	[0, 0.4317, 0.417, 0.246, 0.239, 0.277, 0.254, 0.261, 0.246]	[0, 1.134, 0.847, 0.979, 0.998, 0.923, 0.855, 0.819, 0.754]	[0, 17.544, 14.808, 13.961, 12.988, 13.581, 13.528, 13.636, 12.908]	[nan, 0.639, 0.604, 0.219, 0.127, 0.501, 0.665, 0.448, 0.527]
	[213.4838, 15.479, 86.927, 65.485, 53.737, 43.115, 37.417, 29.018, 22.416]	[0, 0.4317, 0.417, 0.263, 0.243, 0.281, 0.268, 0.254, 0.266]	[0, 1.135, 0.847, 0.965, 1.002, 0.920, 0.883, 0.812, 0.749]	[0, 17.544, 14.808, 14.262, 13.079, 13.497, 12.535, 13.337, 13.417]	[nan, 0.639, 0.604, 0.149, - 0.183, 0.408 - 0.002, 0.519, 0.349]
	[242.483, 144.392, 110.491, 83.074, 63.351, 51.756, 43.715, 35.683, 28.795]	[0, 0.432, 0.257, 0.263, 0.298, 0.265, 0.255, 0.273, 0.278]	[0, 1.135, 1.166, 0.965, 0.897, 0.840, 0.781, 0.814, 0.751]	[0, 17.544, 12.817, 14.262, 13.525, 12.853, 12.804, 13.770, 13.5578]	[nan, 0.639, 0.385, 0.527, 0.250, 0.358, 0.034, 0.479, 0.677]
	[271.483, 168.1704, 135.181,	[0, 0.432, 0.249, 0.279,	[0, 1.135, 1.105, 0.942,	[0, 17.544, 12.695, 14.432,	[nan, 0.639, 0.4156,

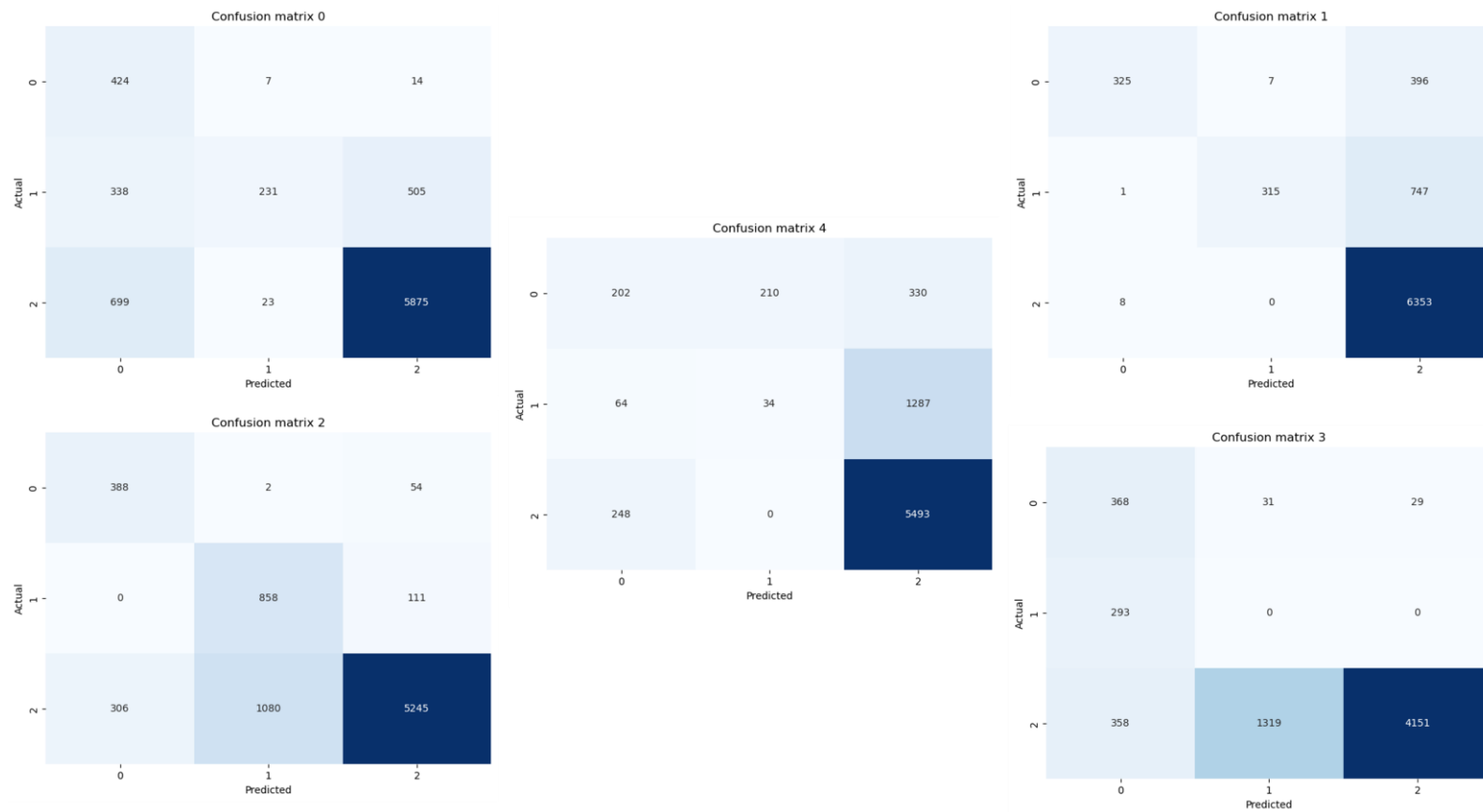
'mBESTest Score', 'Age', 'Height (m)', 'Weight (kg)', 'Gender', 'Practice sports']	102.790, 77.669, 58.897, 50.7048, 41.341, 34.622]	0.288, 0.329, 0.294, 0.307, 0.300]	0.895, 0.842, 0.836, 0.821, 0.687]	15.080, 15.608, 14.824, 15.492, 14.524]	0.553, 0.033, 0.534, 0.238, - 0.132, 0.459]
	[300.483, 191.532, 149.193, 115.899, 90.129, 75.110, 56.337, 45.601, 37.646]	[0, 0.432, 0.417, 0.270, 0.288, 0.282, 0.324, 0.327, 0.329]	[0, 1.135, 0.847, 0.943, 0.895, 0.782, 0.746, 0.722, 0.643]	[0, 17.544, 14.808, 14.407, 15.080, 14.808, 16.701, 17.882, 18.719]	[nan, 0.639, 0.604, 0.396, 0.398, 0.344, - 0.179, 0.488, 0.410]
	[329.483, 199.714, 154.030, 120.608, 101.460, 78.093, 59.314, 47.334, 38.820]	[0, 0.432, 0.417, 0.279, 0.250, 0.282, 0.324, 0.327, 0.329]	[0, 1.135, 0.847, 0.942, 0.992, 0.782, 0.746, 0.722, 0.643]	[0, 17.544, 14.808, 14.432, 13.484, 14.808, 16.701, 17.882, 18.719]	[nan, - 0.639, 0.604, - 0.002, - 0.058, 0.344, 0.123, 0.363, 0.492]
	[329.483, 199.714, 154.030, 120.608, 101.460, 78.093, 59.314, 47.334, 38.820]	[0, 0.432, 0.417, 0.279, 0.250, 0.282, 0.324, 0.327, 0.329]	[0, 1.14, 0.847, 0.942, 0.992, 0.782, 0.746, 0.722, 0.643]	[0, 17.544, 14.808, 14.432, 13.484, 14.808, 16.701, 17.882, 18.719]	[nan, - 0.639, 0.604, - 0.002, - 0.058, 0.344, 0.123, 0.363, 0.492]

Appendix E.

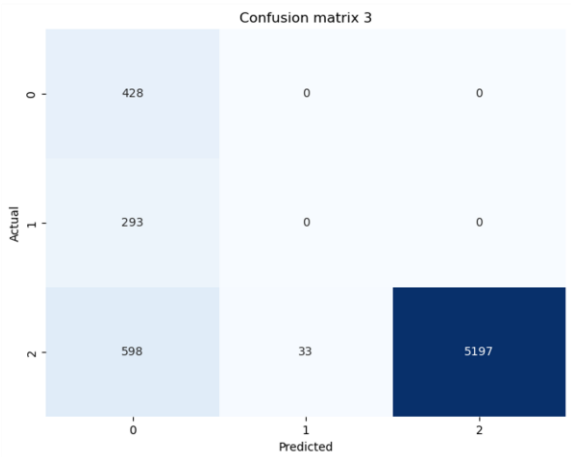
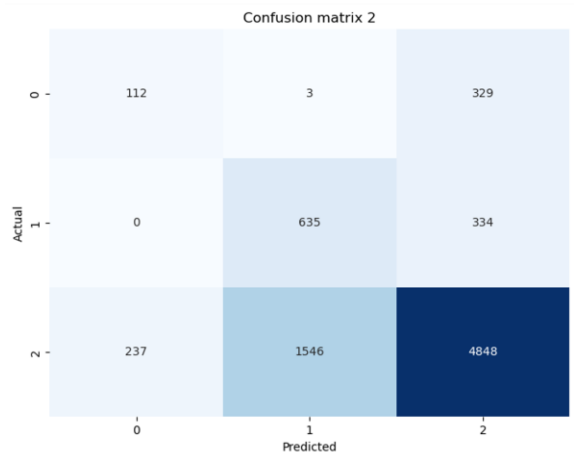
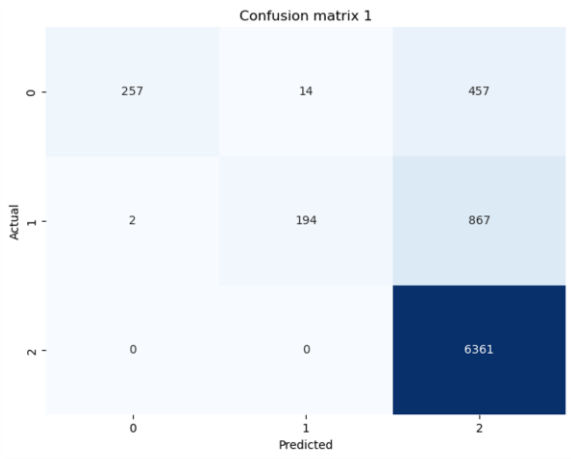
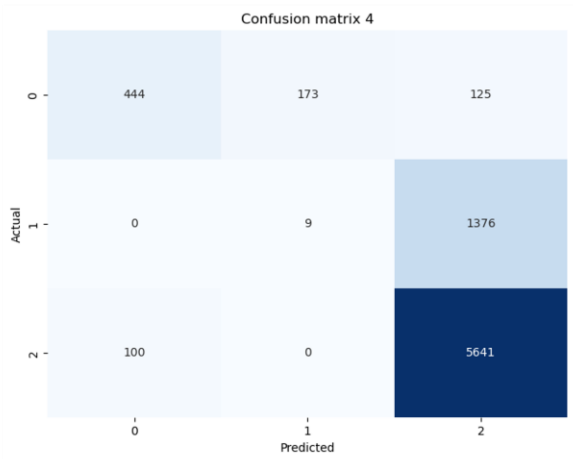
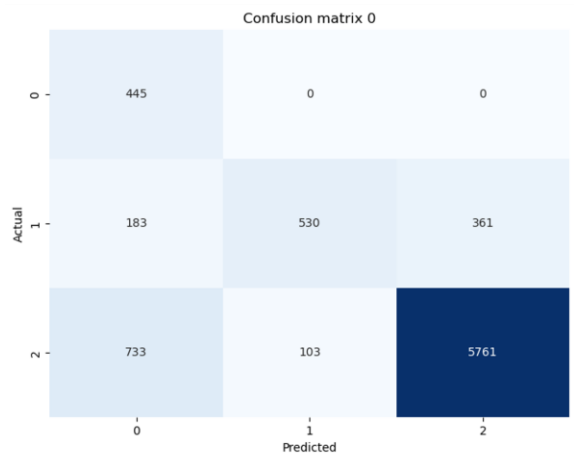
In this section are displayed the confusion matrixes for Methodology 2 for Acceleration and Quaternions as input data.

Appendix E. Confusion matrix. 1) Acceleration as Input Data. 2.) Quaternions as Input Data.

1 Acceleration as Input Data.



2. Quaternions as Input Data

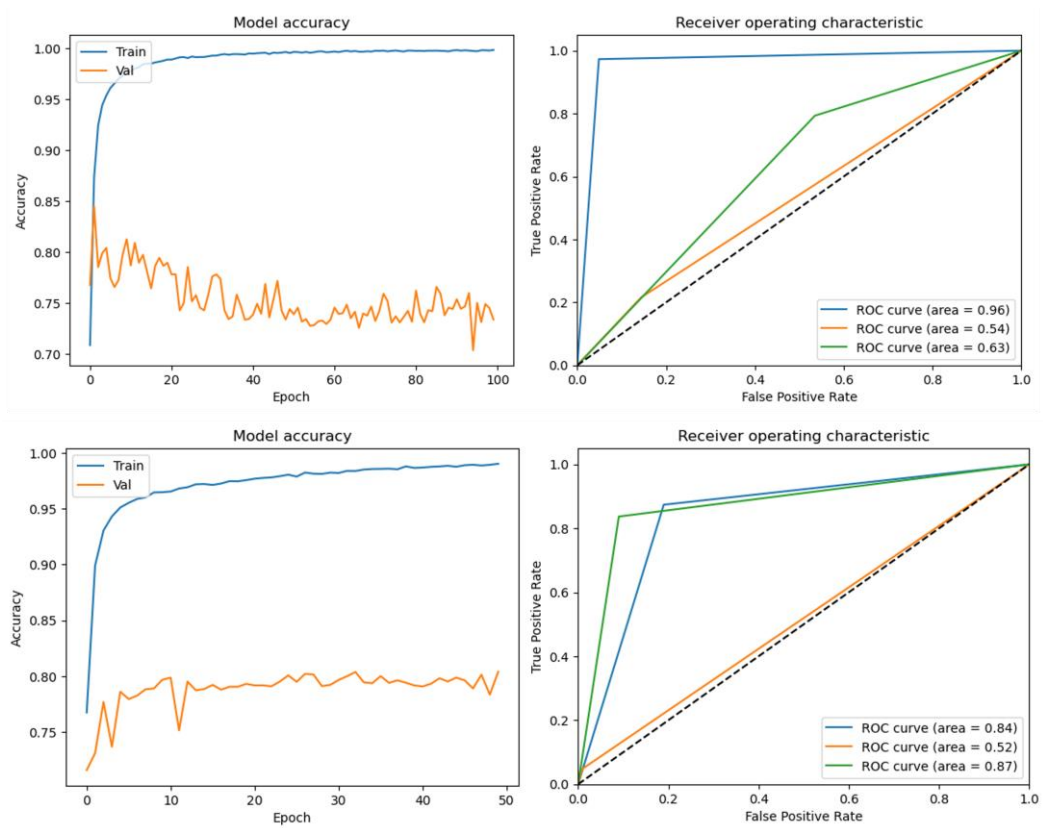


Appendix F.

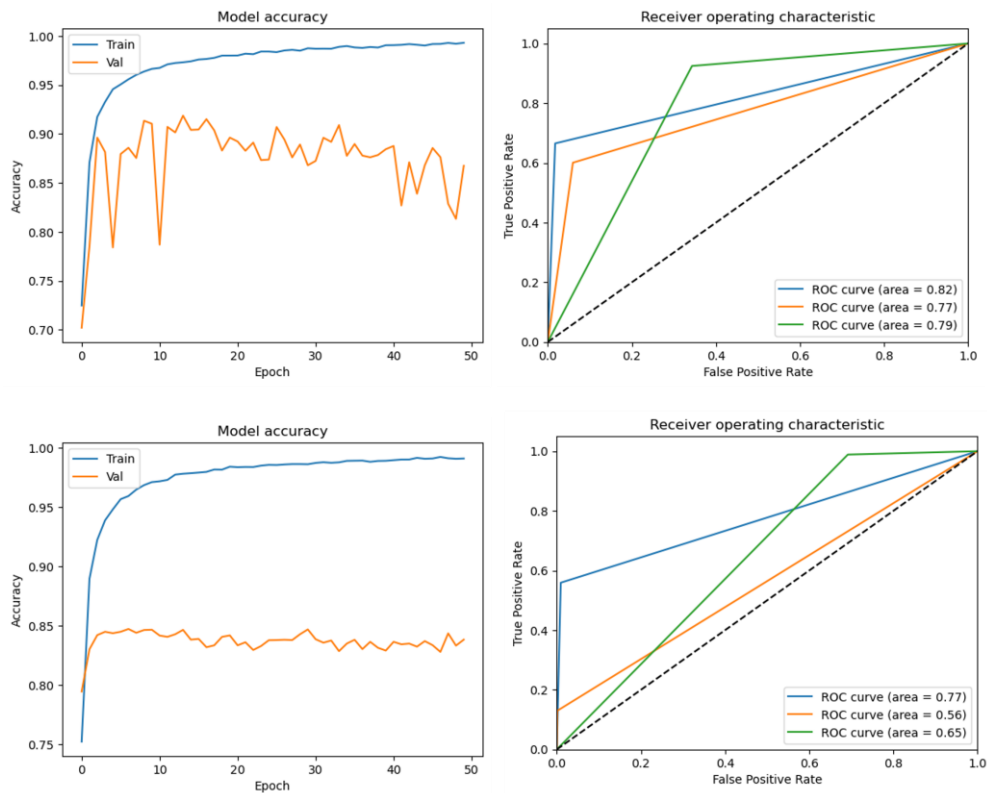
In this section are displayed the model accuracy and ROC curves for each fold corresponding to the information of 6 sensors only.

Appendix F. Accuracy and ROC curves per fold for information of 6 sensors.

Fold 1 and 2



Fold 3 and 4



Fold 5

