

## Article

# Construction Tasks Electronic Process Monitoring: Laboratory Circuit-Based Simulation Deployment

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**Abstract:** The domain of data processing is essential to accelerate the delivery of information based on electronic performance monitoring (EPM). The classification of the activities conducted by craft workers can enhance the mechanisation and productivity of activities. However, research in this field is mainly based on simulations of binary activities (i.e., performing or not performing an action). To enhance EPM research in this field, a dynamic laboratory circuit-based simulation of ten common constructions activities was performed. A circuit feasibility case study of EPM using wearable devices was conducted, where two different data processing approaches were tested: machine learning and multivariate statistical analysis (MSA). Using the acceleration data of both wrists and the dominant leg, the machine-learning approach achieved an accuracy between 92 and 96%, while MSA achieved 47–76%. Additionally, the MSA approach achieved 32–76% accuracy by monitoring only the dominant wrist. Results highlighted that the processes conducted with manual tools (e.g., hammering and sawing) have prominent dominant-hand motion characteristics that are accurately detected with one wearable. However, free-hand performing (masonry), walking and not operating value (e.g., sitting) require more motion analysis data points, such as wrists and legs.

**Keywords:** electronic performance monitoring; wearable devices; process modelling; machine learning; multivariate statistical analysis



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## 1. Introduction

The construction industry (CI) is a significant player in the world economic scenario, as construction-related spending accounts for 13% of the global gross domestic product (GDP) [1]. However, despite its importance, this sector has shown weak productivity growth at a global scale [2], averaging a 1% annual productivity increase since 1997 [1]. Crafts and trade workers comprise 56% of the sector's employment at the European Union level [3]. Innovation is required to mitigate the impact of workforce shrinkage on the industry, boosting labour productivity on site. To this end, there is an increased relevance in monitoring the industry's primary productive workforce, justifying its importance as a research topic, which is aligned with the natural interests of companies [4] and the digitalisation and automation trends of Construction 4.0 [5,6]. Through this monitoring, companies can better evaluate their return on investment [4,7,8], while also providing supervisors with better information to support workforce development, training and deployment [5]. Authors refer to this monitoring and performance measurement as electronic performance monitoring (EPM) [8–10].

As such, the current technological advances enable new, more reliable methods of data collection, allowing for the real-time monitoring of construction activities. These methods are supported by recent innovations in micro and nanotechnology that enable the sustained

assessment of each worker's task process. The systematic control of construction operations can bring immediate awareness of specific aspects of undergoing activities, enabling better decision making [11] and the assessment of the project's productivity in order to increase its performance [12]. Additionally, on-site labour productivity can be correlated with carbon dioxide (CO<sub>2</sub>) emissions and the generation of sanitary wastewater [13]. In fact, according to Mojahed and Aghazadeh, in the context of construction engineering, productivity is mainly related to the performance achieved within each work activity [14]. Finally, digital twins approaches focusing on managing production in a construction set are vital for the monitoring of construction sites [15,16].

The present research aims to assess this EPM in multiple construction tasks, using wearable devices, machine-learning and multivariate statistical analysis (MSA) data processing tools. The objectives of this work are the following:

- Simulate a near-real scenario in which ten different construction activities are performed;
- Deploy EPM, using wearable devices, and investigate options to reduce the number of devices overseeing the activities' characteristics;
- Classify the activities, grouping them over a process analysis;
- Analyse the data with two distinct approaches, namely, machine learning and MSA, comparing the acquired results.

## 2. Background

Workforce activity classification through wearable devices as inertial measurement units (IMUs) is performed using different sensor combinations, namely: accelerometer [17–21]; accelerometer plus gyroscope [22–26]; and accelerometer, gyroscope, plus magnetometer [27–29]. Additionally, IMUs devices are positioned over multiple body parts [17,20,27] or on different body parts, such as: the spine [30,31]; arm [22–25,28]; arms and waist [21,32]; wrist [18,19]; and wrist and leg [26,33].

Labour process modelling based on workforce motion is more commonly applied in manufacturing working design than in the CI, with few studies targeting a process analysis approach in the CI [21,32]. The approach of modelling and measuring manual work systems sets the way for a comprehensive understanding of construction labour motion productivity. The process flow literature has five classes of activities that comprise all production tasks [34–36]:

- Operation (performing work dealing with products), symbolised by a circle [35,36];
- Inspection (performing quality control work), illustrated by a square [35,36];
- Delay (waiting time, do not advance work progress), illustrated by capital "D" letter [35,36];
- Transportation (moving products), illustrated by an arrow [35,36];
- Storage (used for long-range storage) illustrated by a triangle [35,36].

The productive state addresses the workforce performance during the development of tasks, which can be either Productive (also referred to as Direct or Effective) work, Contributory (also referred to as Support) work or Nonproduction (also referred to as Ineffective) work [37]. This concept was applied by Refs [21,32,38] to cluster construction activities over Effective–Support–Ineffective work. A motion productivity model establishes nine processes to map craft workforce on-site tasks [5], as presented:

- Free-hand performing (FHP), Operation, e.g., setting a brick;
- Auxiliary tools (AUT), Inspection, e.g., using a spirit level;
- Manual tools (MNT), Operation, e.g., using a trowel;
- Electric/Electronic tools (EET), Operation, e.g., using a drill;
- Machines operation (MOP), Operation, e.g., using a backhoe;
- Robotic automation (RBA), Operation, e.g., robotic bricklaying arm;
- Do not operate value (IDL), Delay, e.g., chatting and resting;
- Walking (WLK), Delay, e.g., going to the WC;

- Carrying, (CAR), Transportation/Storage, e.g., products, equipment.

Table 1 presents studies targeting construction tasks activity or process recognition. The maximum number of activities analysed in a single study totals eight activities. It is also observed that, on average, six to seven individuals (subjects) perform the activities. Most studies performed simulations (eleven out of thirteen), while only two experienced a more realistic simulation scenario in a training centre. For clarity, a binary analysis can be identified when only one action is evaluated against another action or an idleness state (stopped).

**Table 1.** Studies on activity/process recognition.

Ref.	On-Site Experiment?	Year	Subjects	Activity/Process Recognition
[22]	No, simulation on a binary approach	2016	4	(1) Cutting Lumber; (2) Transportation; (3) Installation. <b>Category 1</b> (1) Sawing; (2) Idling. <b>Category 2</b> (2) Idling; (3) Hammering;
[24]	No, simulation on a binary approach	2015	4	(4) Turning a wrench. <b>Category 3</b> (2) Idling; (5) Loading sections into a wheelbarrow; (6) Pushing a loaded wheelbarrow; (7) Dumping sections from a wheelbarrow; (8) Returning an empty wheelbarrow.
[23]	No, simulation on a binary approach	2016	4	(1) Cutting Lumber; (2) Transportation; (3) Installation. <b>Category 1</b> (1) Sawing; (2) Idling. <b>Category 2</b> (2) Idling; (3) Hammering;
[25]	No, simulation on a binary approach	2018	4	(4) Turning a wrench. <b>Category 3</b> (2) Idling; (5) Loading sections into a wheelbarrow; (6) Pushing a loaded wheelbarrow; (7) Dumping sections from a wheelbarrow; (8) Returning an empty wheelbarrow.
[39]	No, simulation on a binary approach	2016	4	<b>Category 1</b> (1) Sawing; (2) Idling. <b>Category 2</b> (2) Idling; (3) Hammering; (4) Turning a wrench. <b>Category 3</b> (2) Idling; (5) Loading sections into a wheelbarrow; (6) Pushing a loaded wheelbarrow; (7) Dumping sections from a wheelbarrow; (8) Returning an empty wheelbarrow.

Table 1. Cont.

Ref.	On-Site Experiment?	Year	Subjects	Activity/Process Recognition
[26]	No, simulation (not possible to infer the method)	2018	9	(1) Standing; (2) Walking; (3) Squatting; (4) Cleaning up the template; (5) Fetching and placing rebar; (6) Locating the rebar; (7) Binding rebar; (8) Placing concrete pads.
[28]	No, simulation (static, performing actions over a table/workstation)	2018	8	(1) Grabbing tool/part; (2) Hammering nail; (3) Using power screwdriver; (4) Resting arm; (5) Turning screwdriver; (6) Using wrench.
[18]	No, simulation (in a training centre with workers)	2016	5	(1) Spreading mortar; (2) Bringing and laying blocks; (3) Adjusting blocks; (4) Removing remaining mortar.
[19]	No, simulation (in a training centre with workers)	2019	10	(1) Spreading mortar; (2) Bringing and laying blocks; (3) Adjusting blocks; (4) Removing remaining mortar.
[32]	Yes, on-site	2012	-	(1) Effective work; (2) Contributory work; (3) Ineffective work.
[21]	Yes, on-site	2014	20	(1) Effective work; (2) Contributory work; (3) Ineffective work.
[40]	No, simulation (not possible to infer the method)	2011	-	(1) Fetching and spreading mortar; (2) Fetching and laying brick; (3) Filling joints.
[41]	No, simulation on a binary approach	2020	8	(1) Screwing; (2) Wrenching; (3) Lifting; (4) Carrying.

Several mathematical and statistical methods can be used to process and analyse the data. In most cases, these methods are used in conjunction with the univariate and multivariate analyses [42] and Monte Carlo simulation [38]. Dynamic analysis methods and neural networks are also widely used. There is a trend for applying artificial intelligence (AI) when faced with the large amounts of data collected by electronic devices to process such information quicker and more autonomously. Academic studies focusing on the classification of human activities/actions develop algorithms based on machine learning, including deep-learning [28,43] and traditional approaches [19,20,44]. Machine learning is a subset of AI and can be seen as an autonomous and self-teaching system for training algorithms to find patterns and subsequently use this knowledge to make predictions about new data [45,46]. The domain of data processing is essential to accelerate the delivery of information based on EPM: the faster and more autonomous the data processing, the more agile the delivery of solutions.

### 3. Method

#### 3.1. Research Design

As highlighted above, most studies on activity and process recognition showcase a binary approach (performing/not performing an activity) [22–25,39,41], with few experiments conducted on site [21,32]. To fill this gap, the present research proposes a laboratory circuit with multiple activities, emulating on-site conditions for testing EPM deployment.

A laboratory environment provides a more controlled and labour-saving environment to record and label the actions, as well as test the hardware solutions. Figure 1 presents the data collection and analysis flow chart to clarify the validation approach of the different cases. The main goal is to test and validate the laboratory circuit-based simulation deployment and compare and evaluate two data analysis approaches, assessing their feasibility and performance accuracy.

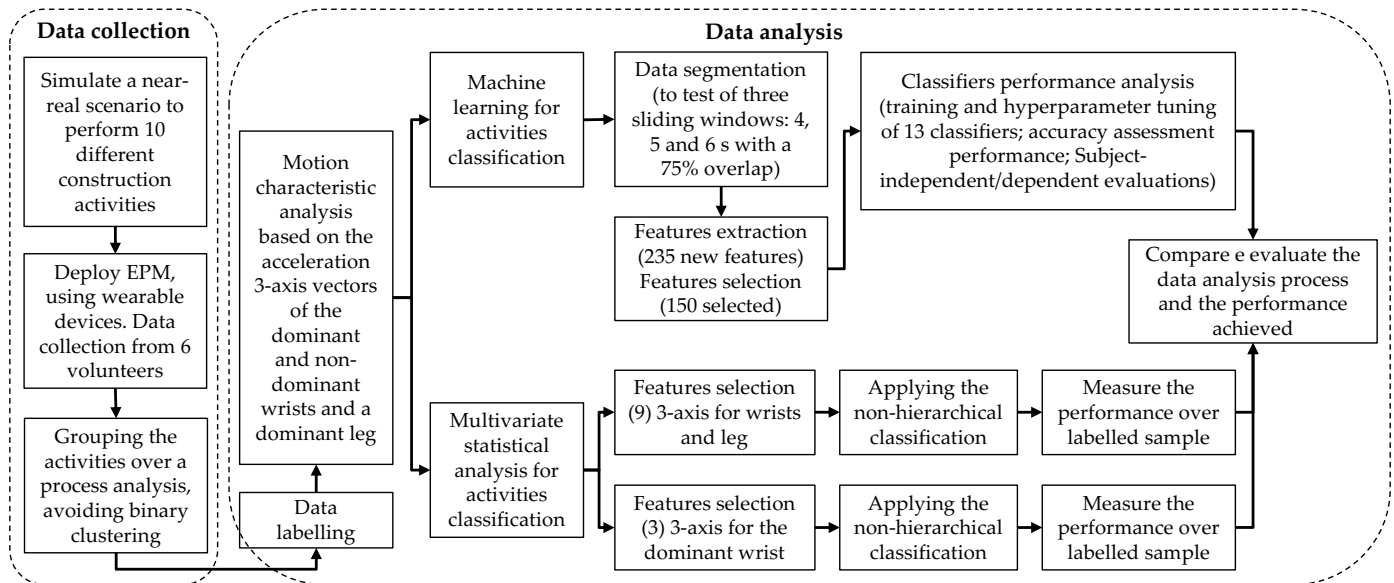


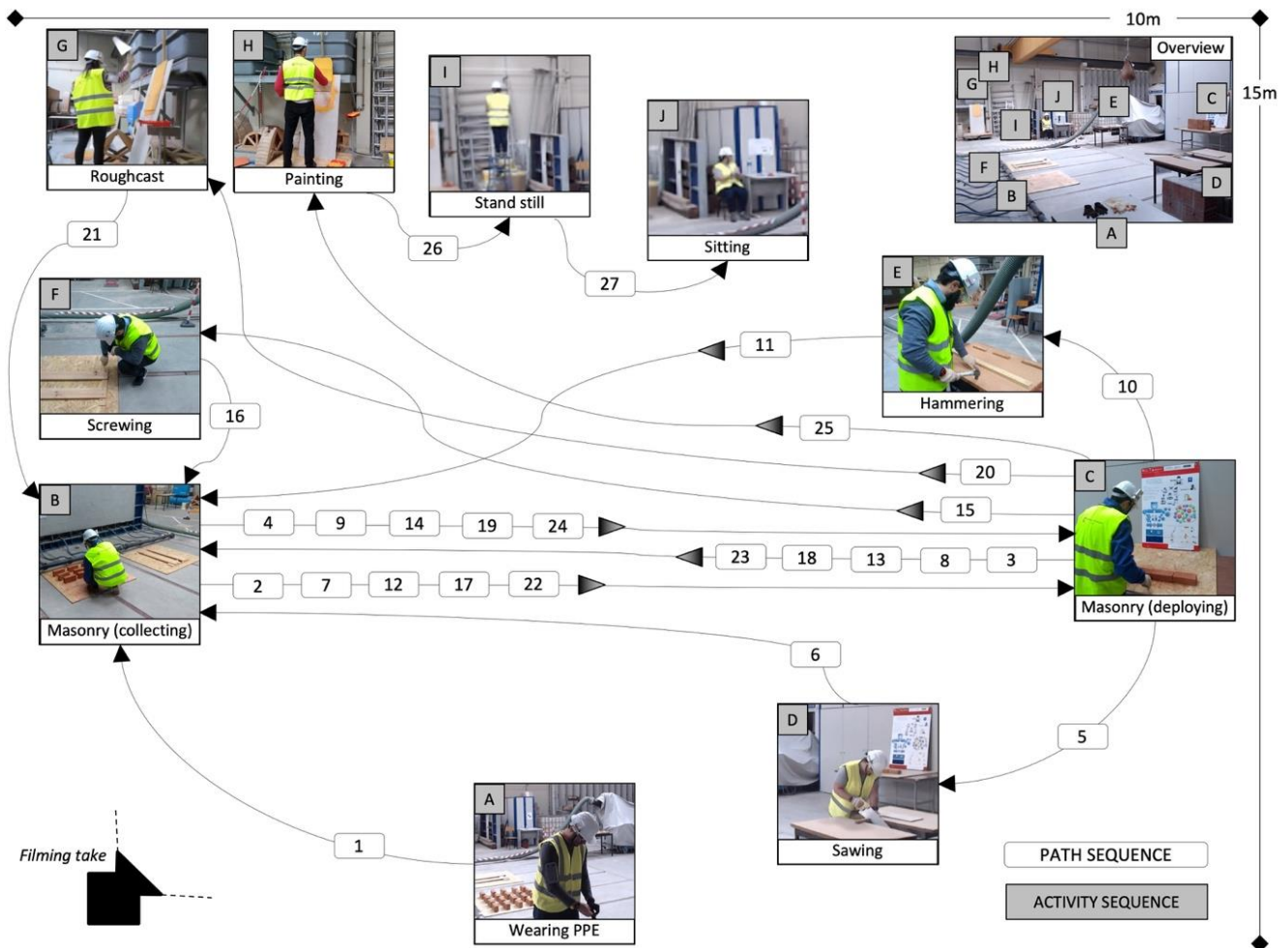
Figure 1. Research flow chart.

### 3.2. Data Collection

For an efficient performance monitoring of the construction craft workforce, it is essential to at least assess the hand tasks, the walking–travelling and the idleness. To this end, a circuit concept was established to simulate an interactive work scenario seen in a typical on-site construction project. This circuit purposely aimed to avoid a binary analysis, as it is the authors’ opinion that such an approach does not properly reflect a construction worker’s behaviour. For this reason, basic daily work activities were selected, which are part of the daily life of workers in different functions. It can be inferred that, given the role of a specific worker, his/her actions can be previously mapped, which would facilitate activity classification. Additionally, according to Adrian (2004), at least 50% of the workforce time on site is spent on non-productive activities (e.g., walking, drinking water, talking to co-workers) [37]. A total of six volunteers were equipped with three devices, two on both wrists and one on the dominant leg’s ankle. The inertial measurement units (IMU, similar to watches) devices collected 3-axis data at a sampling frequency of 100 Hz with a 1 s epoch output. Each data point is thus represented as a vector containing the timestamp of the reading and nine acceleration values (one for each axis of the three accelerometers).

Figure 2 shows the circuit deployed in a 150-square-meter indoor laboratory. The circuit was composed of work areas where the volunteers interactively performed the existing 10 activities. The volunteers walked from station to station to perform these activities, walking/travelling around the stations, assumed with letters in the figure. As well, a path sequence was pointed out as evidenced with the numbers; however, the volunteers had the option of carrying two or four bricks at once and shortening the travel between actions B (Masonry collection) and C (Masonry deployment).





**Figure 2.** Laboratory circuit with the path and activity sequence, the first set by the numbers and the following by the letters.

### 3.3. Data Analysis

Figure 3 presents the deployed method. After completing the circuit containing ten construction activities, each simulation had its actions labelled every second. These data were then processed and evaluated by two different methods. A graphical analysis of the accelerations collected during each activity summarised the analysis. Finally, a qualitative analysis of the two methods was provided. The data were labelled manually using a synchronised video recording of the circuit. The data points of each activity were:

- Painting, MNT—Manual tools (1562);
- Sawing, MNT—Manual tools (1466);
- Hammering, MNT—Manual tools (1419);
- Walking, WLK—Walking (1411);
- Masonry, FHP—Free-hand performing (863);
- Screwing, MNT—Manual tools (759);
- Sitting, IDL—Do not operate value (624);
- Roughcasting, MNT—Manual tools (621);
- Standing still, IDL—Do not operate value (296);
- Wearing personal protective equipment (PPE), IDL—Do not operate value (287).

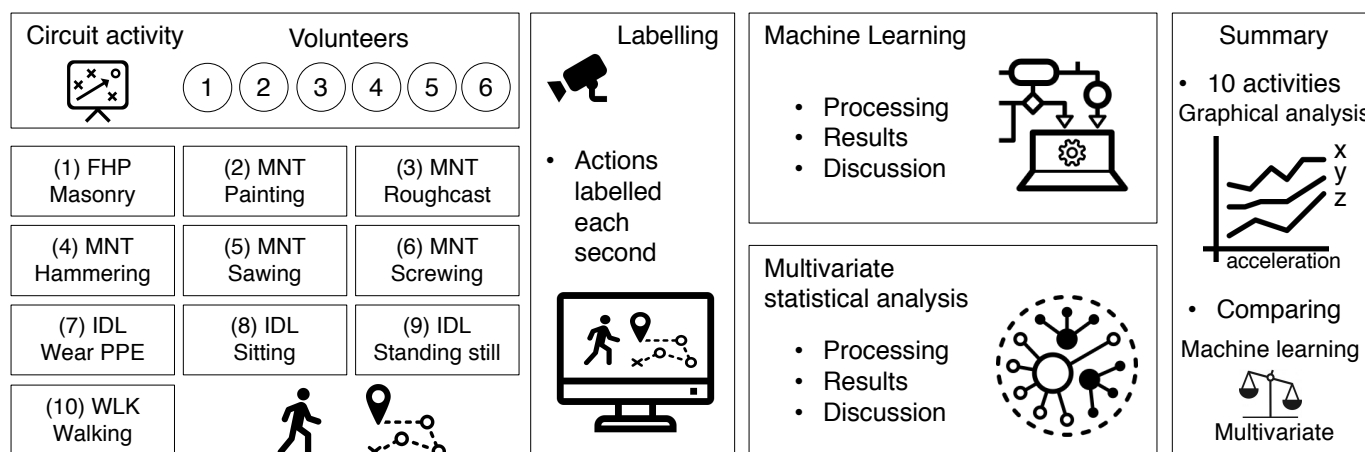


Figure 3. Laboratory experiment method.

Next, the activities were clustered into three small mixed groups based on the process characteristics and the number of data points. First, a mixed group was established with the only “free-hand performing” activity (Masonry) plus two “manual tools” processes (Painting and Roughcasting). A second contained just “manual tools” (Hammering, Sawing and Screwing). A third was composed of “do not operate value” (Wearing PPE; Sitting; Standing still) and “walking” (Walking).

Additionally, the formation of the three groups of analysis with different processes and their respective activities was based on diversification to evaluate the variability in the classification accuracy through the different groups of activities with different motion patterns. However, the group “free-hand performing (Masonry) plus two manual tools (Painting and Roughcasting)” had a mix of motion activities; the masonry action had multiple two hands and body motion activities, while painting and roughcasting had almost static body motion with a prevalence of high-frequency motions on the predominant hand and only a few motions on the non-dominant hand, supporting the actions.

In the group “manual tools (Hammering, Sawing and Screwing)”, there was a uniqueness of actions with hand tools and non-movement characteristics of the legs. Additionally, a predominance of high frequency on the predominant hand motions could be noted, which was only supported by a quasi-static motion of the non-dominant hand. However, the three activities demanded very peculiar and distinguished predominant hand motions between them.

Finally, the group “do not operate value (Wearing PPE, Sitting, Standing still) plus walking (Walking)” mixed the walking movement with resting actions and some unusual movement activities, such as putting on protective equipment (e.g., gloves, glasses, helmet).

A total of 155 min of activities was monitored. The process of labelling the actions (second by second) took approximately 26 h. Table 2 shows the number of points (variables) collected by the 3-axis accelerometers positioned in three locations on the volunteers’ bodies.

Table 2. Data collected.

		Masonry, Painting and Roughcasting	Hammering, Sawing and Screwing	Wearing PPE, Sitting, Standing Still, Walking	Total
Experiment Timing	seconds	3046	3644	2618	9308
	minutes	51	61	44	155
Labelling Timing	minutes	508	607	436	1551
Acceleration data points	Wrists and Leg	27,414	32,796	23,562	83,772
	Wrist (dominant)	9138	10,932	7854	27,924

For data processing, the pre-labelling of activities is necessary. First, the classification algorithms used the labelled data for training. Second, pre-labelling enabled quantifying

the accuracy of the analyses. MSA was used to group data according to the characteristics of the variables. Both processes were applied to understand the potential of each method to be used in future applications. In addition, a graphical analysis of the accelerations collected in the 3 axes allowed an assessment of the specific characteristic of each activity, improving the perception of the results obtained by the classification methods.

## 4. Results and Discussion

### 4.1. Acceleration Data

This section presents and discusses the activities' acceleration data characteristics and the results of both processing methods applied for classifying the actions (i.e., machine learning and MSA). A cross-analysis focuses on a deep understanding of the tasks and process motion characteristics. Finally, a qualitative analysis of the processing tools is presented based on the findings.

The clustering of activities was realised by targeting a diverse group of motion characteristics. In the first group, the Masonry activity presented a mix of motions, from loading to laying the bricks. It is possible to observe a variety of accelerations in the three axes (X, Y, Z) in both the dominant and non-dominant hands and the leg. In contrast, the Painting activity has more significant dominant hand motions, with a marked acceleration in the Z direction, with little or no effort in the other hand and legs. Finally, in Roughcasting, dominant hand movements' predominance can be identified with more significant accelerations in the Z and X directions. Figure 4 presents the characteristics of accelerations from dominant and non-dominant wrists, as well as the dominant leg for the three activities, making it possible to visualise the distinguished motion patterns. It can be inferred that when classifying these three activities, some misleading results can occur because of the non-linearity of the Masonry activity that might overlap with some motion characteristics captured in the other activities. This becomes even clearer when the classification is based only on the wrist-dominant motions, as the leg variable that will differentiate it from the others is lost, resulting in reduced accuracy.

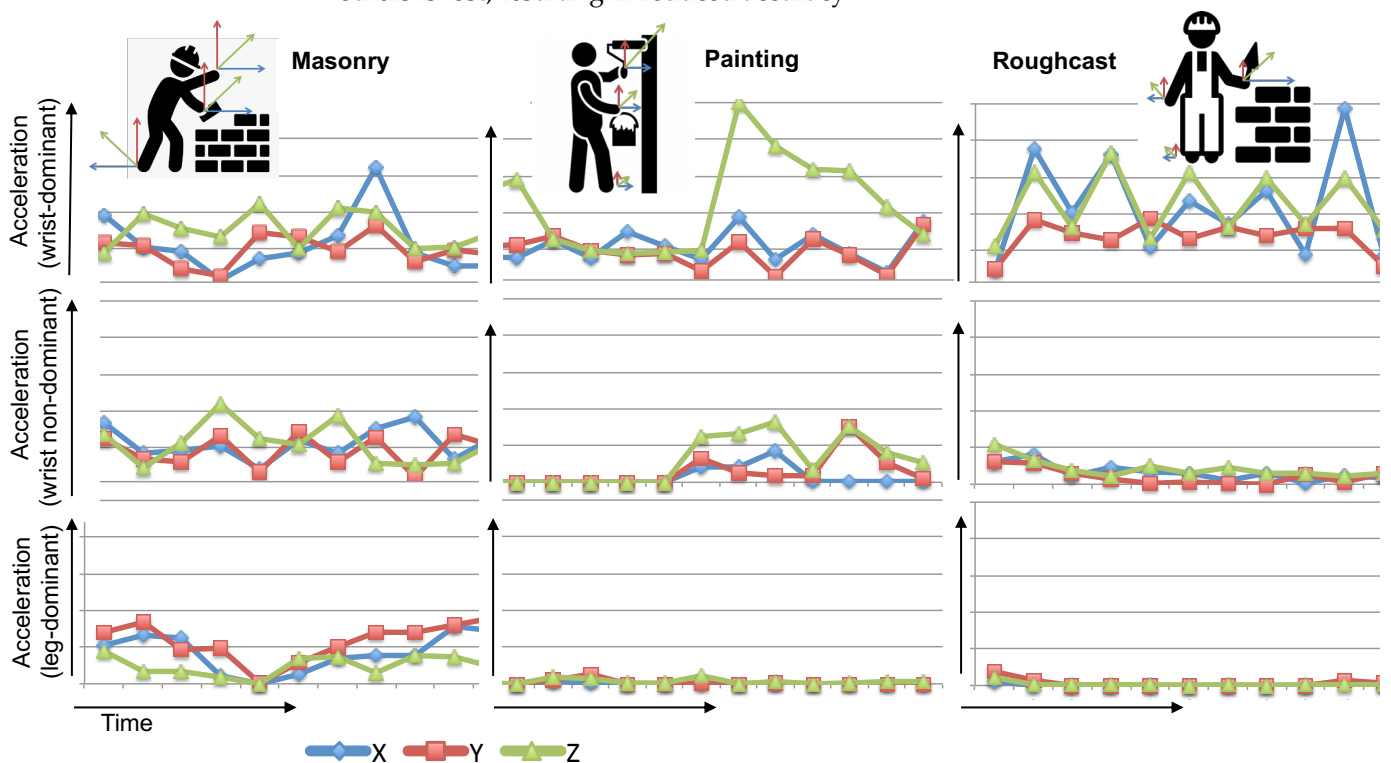
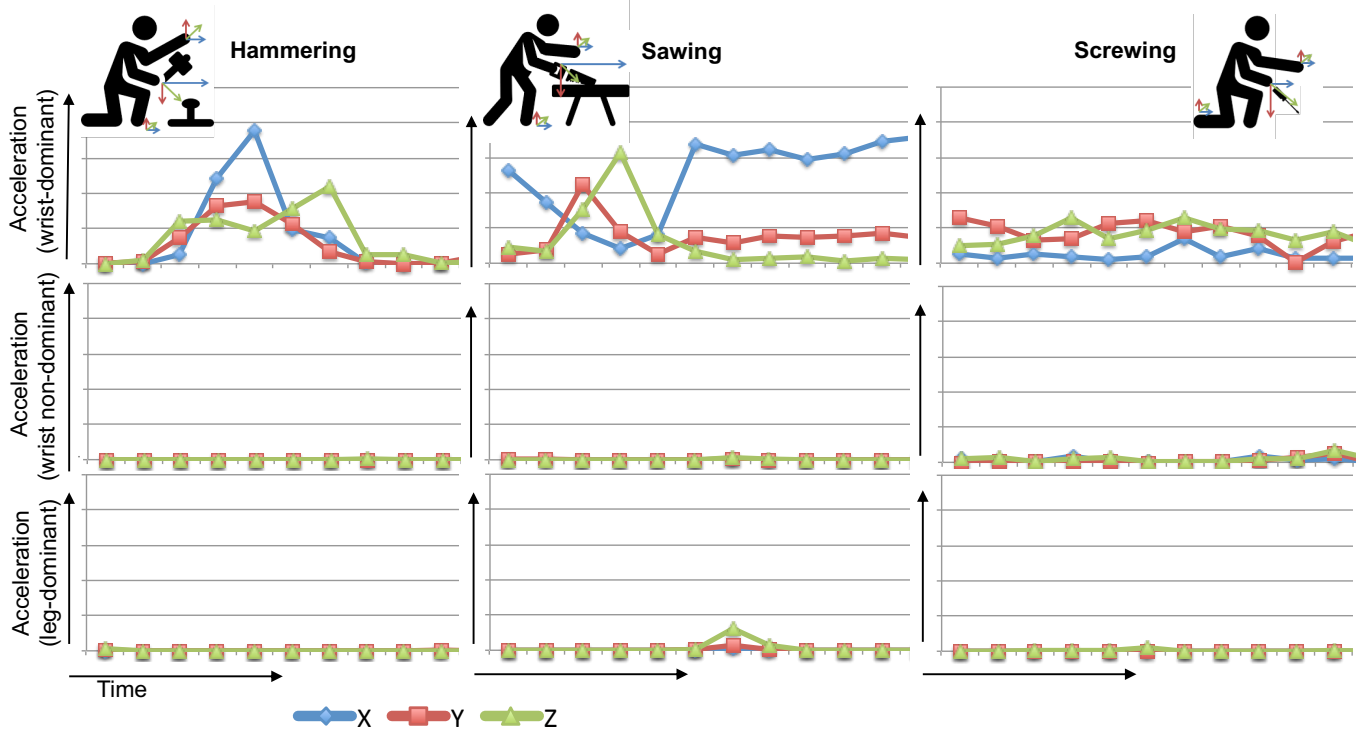


Figure 4. Motion characteristic of Masonry, Painting and Roughcast.

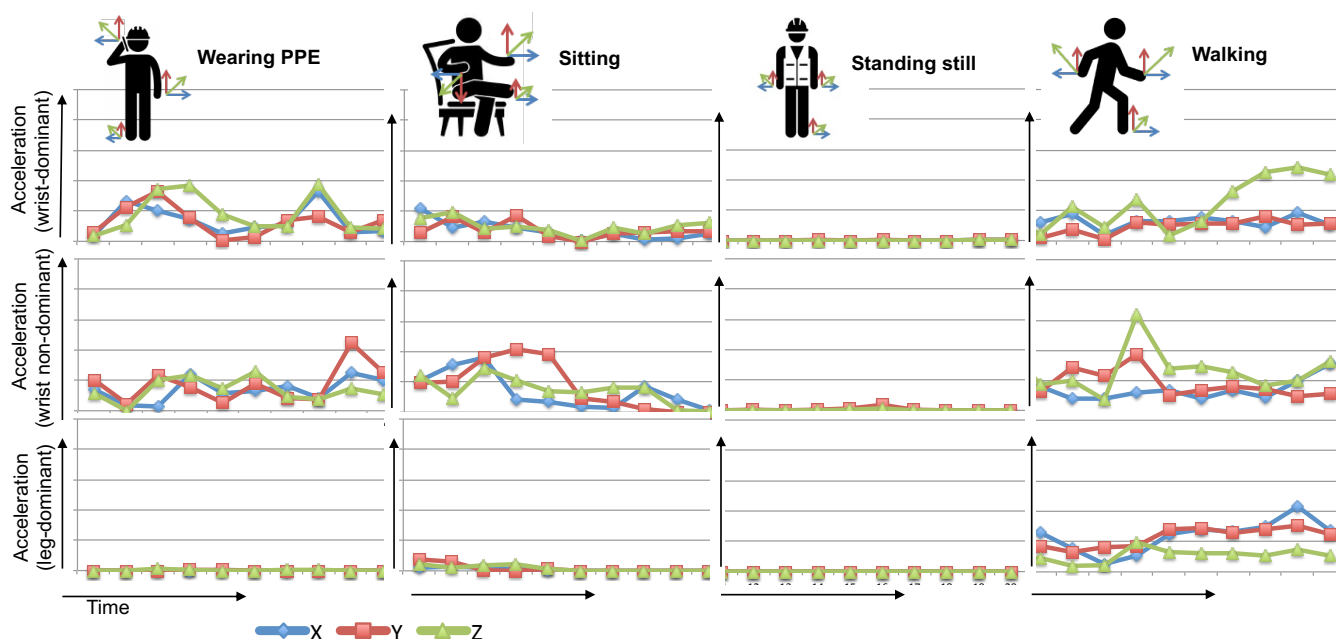


In the second group, a more precise classification/clustering is observed in activities using manual tools. All three activities have similar characteristics: significant dominant hand motions, non-dominant hand support when adjusting the material/element and supporting the body, and virtually no leg motions. The predominance of movements in vectors X and Z stands out in the hammering activity. The predominance of acceleration in the X direction is evident in the Sawing activity. Finally, in the Screwing activity, a linear pattern is seen, with the predominance of vectors Y and Z. This set of activities is presented in Figure 5. It is observed that the accuracy of the classifiers should not be influenced by removing the non-dominant hand and leg data. On the contrary, there is a subtle accuracy increase.



**Figure 5.** Motion characteristic of Hammering, Sawing and Screwing.

Finally, in the last group, except for the Standing still activity, which practically does not present motions with representative accelerations, the other activities are of peculiar motions. For example, volunteers move their hands and legs slightly, even while sitting. When Wearing PPE, no significant leg motions are detected, but the hands have practically random accelerations. When Walking, the limbs' motions and accelerations have a similar cadence in each individual. Machine learning interprets the acceleration patterns more accurately than the other methods used in this study. On the contrary, the simple grouping by multivariate analysis only makes it easy to observe the Standing still state, not evaluating cadences with similar acceleration. The most prominent vectors in each activity are represented in Figure 6 for Wearing PPE, Sitting, Standing still and Walking. When the results are only pertinent to the wrist-dominant data, there are practically no differences in the accuracy. This fact indicates that the wrist-dominant motion detected was peculiar enough to differentiate such different actions.

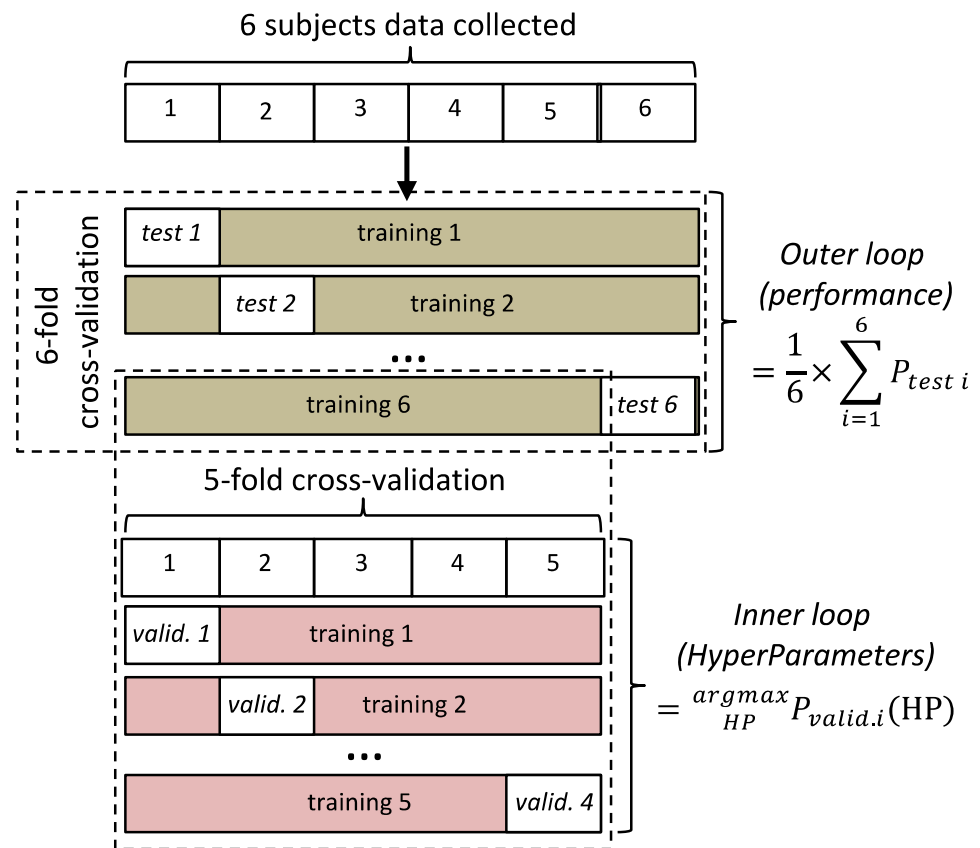


**Figure 6.** Motion characteristic of Wearing PPE, Sitting, Standing still and Walking.

#### 4.2. Machine Learning

After data collection, all information points must be characterised manually for the machine-learning approach, which indicates the need to use video recordings as a reference. These points are the identification and labelling of the type of process or action or motion at each moment of the analysis. Then, the process of classifying the data is carried out, which are commonly divided into groups according to the characteristics of the sample. Afterwards, feature extraction is performed to identify the most useful characteristics to classify each group of actions. Next, the classifiers are selected, and each method's reliability (%) evaluation is performed for the sample. Finally, a set of algorithms can be calibrated to carry out future autonomous analyses.

As previously presented, the ten activities were divided into three groups: Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting); Manual tools (Hammering, Sawing and Screwing); Do not operate value (Wearing PPE, Sitting, Standing still) + Walking (Walking). Several classification conditions were studied, including the ideal time window size (in seconds) to segment the data; the extraction and selection of relevant artificial features; the adjustment of hyperparameters (time windows and parameter grouping masses); and the training and selection of the classifier. As presented in Figure 7, the hyperparameters and classifier selection was based on the best accuracy obtained through a cross-validation approach, using two training loops.



**Figure 7.** Cross-validation approach comprising two training loops.

Finally, the classifiers were tested in a subject-independent (i.e., classifier trained without any test subject data) and -dependent (i.e., classifier trained with a portion of the test subject data) approach for all activities, using the optimal reasonable time window.

Thirteen different classifiers were evaluated, containing both basic models and ensemble methods:

- Basic models: decision tree (DT); K-nearest neighbours (KNN); logistic regression (LR); multilayer perceptron (MLP); multiclass support vector machines (SVM) with different kernels (linear (LSVM), polynomial (PSVM), radial basis function—rbf (RSVM), sigmoid (SSVM)).
- Ensemble methods: random forest (RF); extremely randomised trees (ExT); AdaBoost (AdB); gradient boosting (GrB); majority/hard vote (vote). For the subject-independent assessment approach, windows with different times (4, 5 or 6 s) were applied to each group of activities.

For an analysis of the subject-independent approach, Figures 8–10 show the classifiers' performance (average balanced accuracy) for each group and window combination. Figure 11 presents the average performance of all groups per window, and Figure 12 presents the average performance of all windows per group.

### Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting)

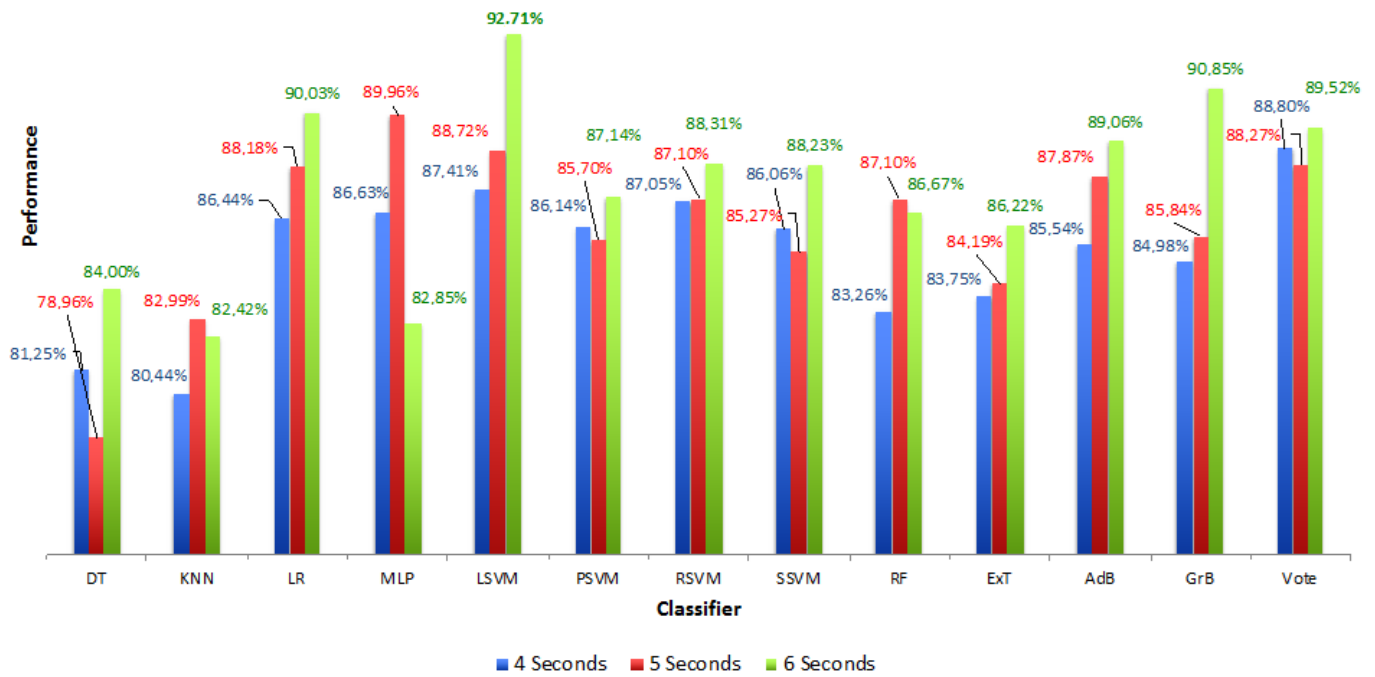


Figure 8. Classifiers’ performance for Masonry, Painting and Roughcasting.

### Manual tools (Hammering, Sawing and Screwing)

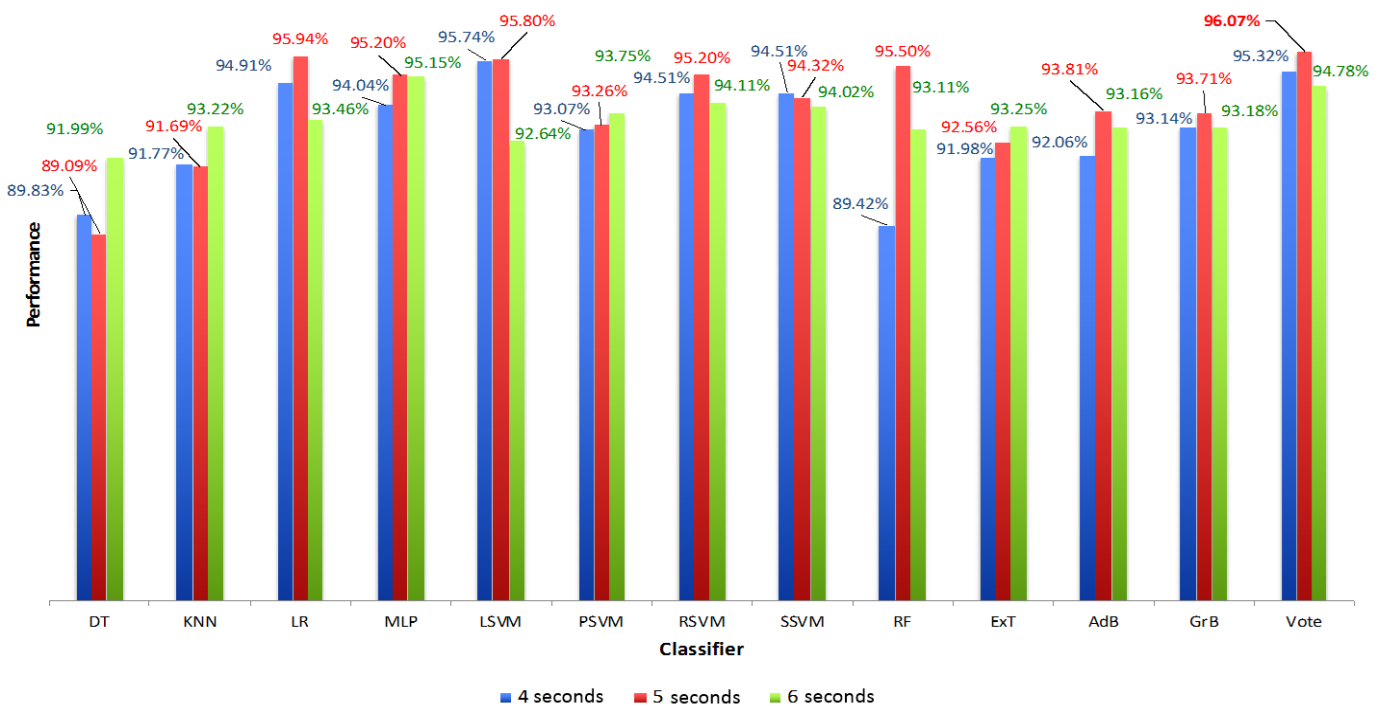


Figure 9. Classifiers’ performance for Hammering, Sawing and Screwing.

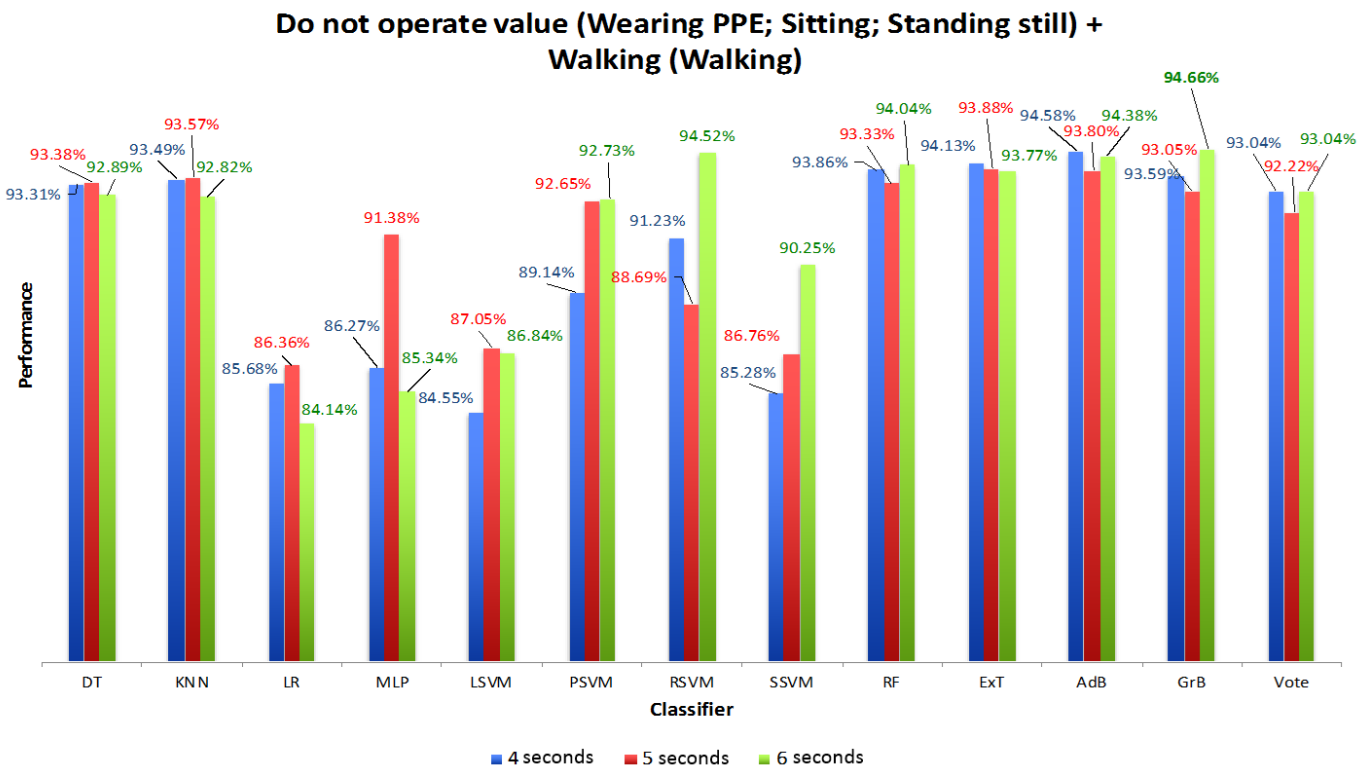


Figure 10. Classifiers’ performance for Wearing PPE, Sitting, Standing still and Walking.

### Classifiers’ average performance for all groups per window

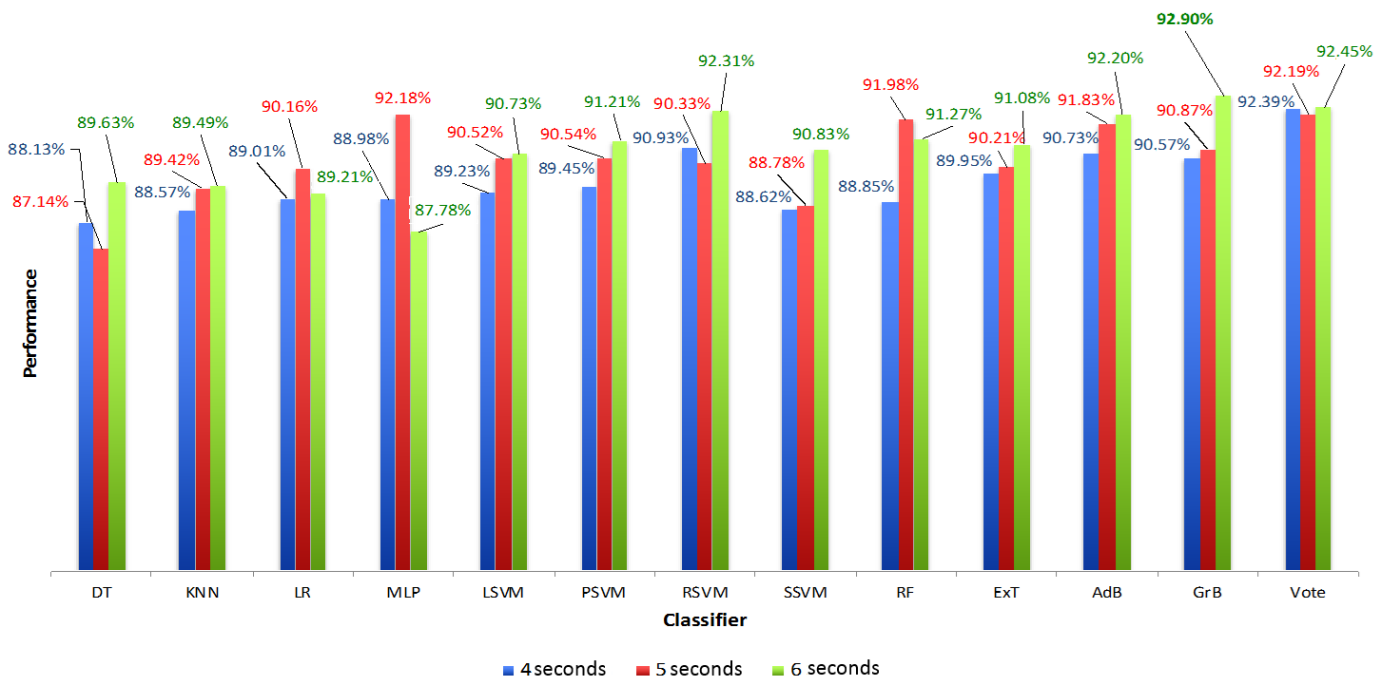
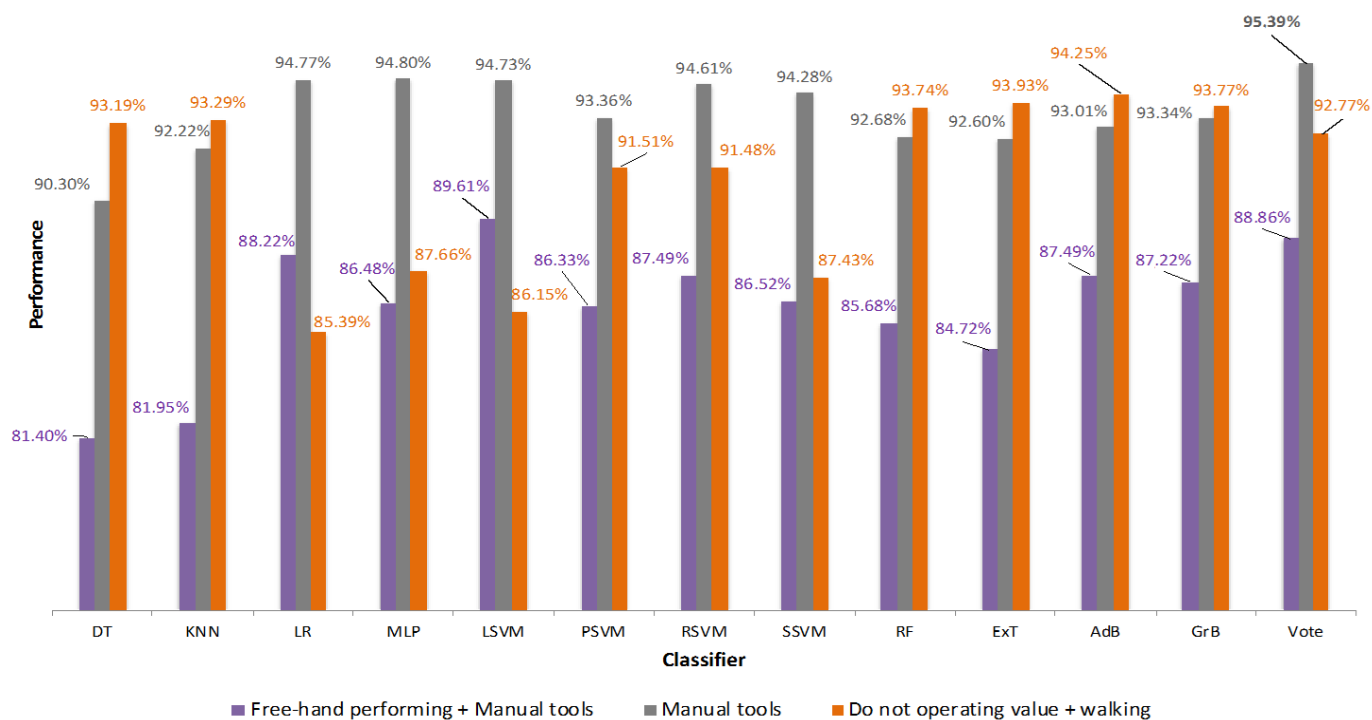


Figure 11. Classifiers’ average performance for all groups per window.



### Classifiers' average performance for all windows per group



**Figure 12.** Classifiers' average performance for all groups per window.

Figure 8 shows the results for the “free-hand performing (Masonry) plus two manual tools (Painting and Roughcasting)” group, where the best performing classifier showcased a 92.71% accuracy (6 s window with the LSVM classifier).

Figure 9 shows the results for the “manual tools (Hammering, Sawing, and Screwing)” group, where the best performance was a 96.07% accuracy for the vote classifier with a 5 s window.

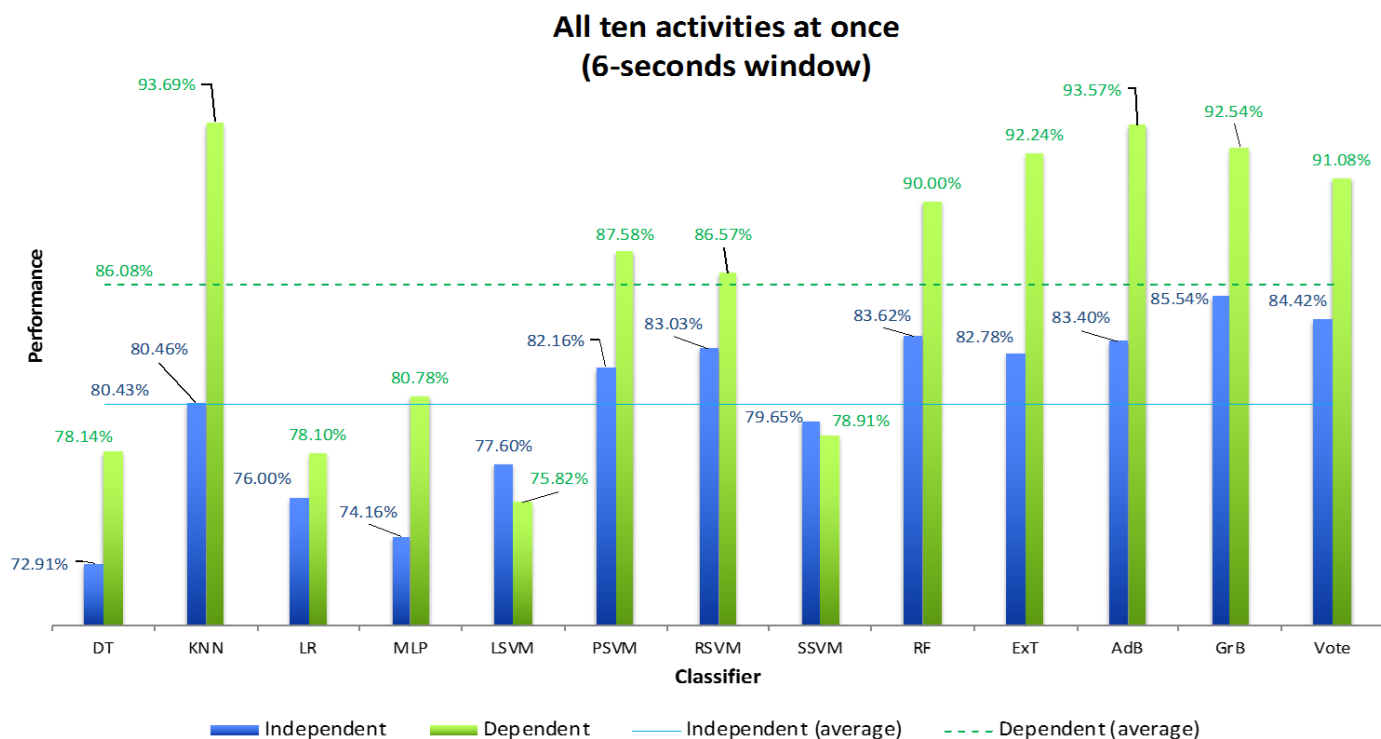
Finally, Figure 10 shows the results for the group “do not operate value (Wearing PPE, Sitting, Standing still) plus walking (Walking)”, where the best performance was achieved for a 6 s window with the GrB classifier—94.66% accuracy.

In summary, all three groups presented a similar range of performance, with all best accuracies at above 92%.

For an analysis of a subject-dependent approach, Figure 13 showcases the performance of all classifiers when applied to all ten activities and a 6 s window. This approach essentially indicates whether and how much the classifier performance would benefit from gathering the training data of new subjects (i.e., workers) before starting to predict their activities. To help compare both approaches, Figure 13 also shows the same analysis for a subject-independent approach, enabling a side-by-side comparison.

As such, from Figure 13, it can be concluded that the KNN classifier achieved the best performance of 93.69%, with the AdB classifier ranking in close second with 93.57%. Both these highest accuracies were achieved for the subject-dependent approach, which reached an average performance of 86.08%, throughout all classifiers. This accuracy is roughly 6% higher than the 80.43% average accuracy achieved by the subject-independent approach. In fact, the subject-independent approach with all activities was also far below the accuracies achieved for each group independently, whose highest values were all above 92%, as previously seen in Figures 8–10. Thus, it can be stated that the division of all activities into smaller groups is vital to increase accuracy, while subject dependence can help boost the accuracy even further.

Nevertheless, even without all favourable conditions, the achieved accuracies are encouraging, with the GrB classifier achieving a maximum of 85.54% when facing all activities and a subject-independent approach (Figure 13).



**Figure 13.** All ten activities at once (6 s window).

#### 4.3. Multivariate Statistical Analysis

The multivariate statistical analysis aims to verify the formation of clusters for the data collected during the experiment. IBM SPSS Statistics (version 25) was the main software tool for statistical calculations. Microsoft Excel was also used for the graphical formatting of data from SPSS. The analysis by non-hierarchical classification allows the evaluation of the cluster's dimensionality formed by the subjects [47], where a synthesis analysis of the mathematical results is carried out concerning the aspects of the three groups of processes and the ten activities: Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting)—three clusters; Manual tools (Hammering, Sawing and Screwing)—three clusters; Do not operate value (Wearing PPE, Sitting, Standing still) + Walking (Walking)—four clusters.

After applying the non-hierarchical classification according to the number of activities in each group, the results are compared with the labelled data to determine the accuracy of these processes. Initially, to group the clusters' activities, only the absolute parameters of the accelerations (in their three axes) collected on the wrists and one leg were used as variables (83,772 data points). However, nine features were used in the analysis. Next, the same process was performed only with the values of the accelerations (three axes) of the volunteers' dominant hands. Thus, the analysis had a third of the number of variables used in the previous case (27,924 data points). However, three features were used in the analysis.

Table 3 presents the set-up requirements for a non-hierarchical classification in Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting) processes and tasks, making three clusters fit with the activities. To group the activities in clusters, the absolute parameters of the accelerations (in their three axes) collected on the wrists and one leg were used as a total of nine variables (27,414 data points).

**Table 3.** Set-up of three clusters.

Output Created		
Input	Active Dataset	DataSet0
	Filter	<none>
	Weight	<none>
Missing Value Handling	Split File	<none>
	N of Rows in Working Data File	3046
	Definition of Missing	User-defined missing values are treated as missing.
Syntax	Cases Used	Statistics are based on cases with no missing values for any clustering variable used. QUICK CLUSTER VAR00006-07-08-09-10-11-12-13-014 /MISSING = LISTWISE /CRITERIA = CLUSTER(3) MXITER(10) CONVERGE(0) /METHOD = KMEANS(NOUPDATE) /SAVE CLUSTER DISTANCE /PRINT INITIAL ANOVA CLUSTER DISTAN.
	Wrist (dominant) 3 VAR	
	Wrist (non-dominant) 3 VAR Leg (dominant) 3 VAR	
Resources	Processor Time	00:00:00.39
	Elapsed Time	00:00:00.00
	Workspace Required	1944 bytes
	QCL_2	Distance of Case from its Classification Cluster Centre

Table 4 presents the interaction history. Iterations stopped because the maximum number of iterations was performed. The maximum absolute coordinate change for any centre is 0.836, and the current iteration is 10. The minimum distance between the initial centres is 584.024. Table 5 shows the distances between the final cluster of activity centres, and Table 6 presents the number of cases in each cluster.

**Table 4.** Interaction history.

Iteration	Change in Cluster Centres		
	Roughcast	Painting	Masonry
1	313.4141	199.5498	246.4082
2	63.2804	25.8395	110.5989
3	26.4273	18.7292	38.7331
4	12.9446	9.3842	15.5661
5	7.7845	5.5610	4.5176
6	3.9339	2.9209	1.3539
7	3.050	2.4074	0.9133
8	1.772	1.3521	0.3767
9	1.1367	0.8386	0.2579
10	0.8516	0.6606	0

**Table 5.** Distances between final cluster centres.

Cluster	Roughcast	Painting	Masonry
Roughcast		159.1544	283.4235
Painting	159.1544		233.6170
Masonry	283.4235	233.6170	

**Table 6.** Number of cases.

Number of Cases in Each Cluster	
Roughcast	1022
Painting	1309
Masonry	715
Valid	3046
Missing	0

In effect, each of the 3046 lines (activities identified in each second) was identified by a cluster. A small extraction of this information is shown in Table 7. Moreover, a true or false analysis was carried out line by line to identify whether the indicated cluster was equal or not to the real label. Thus, when the correct results are totalled, the accuracy of the analysis is determined. Finally, the results for the multivariate analysis of “Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting)” indicated 1855 correct values in 3064, reaching an accuracy of 60.90%. The exact process of clustering only three axes of the dominant hand (9138 data points) achieves 32.50% accuracy. Table 8 presents the set-up requirements for a non-hierarchical classification in Manual tools (Hammering, Sawing and Screwing) process and tasks, creating three clusters of activities. To group the activities into clusters, the absolute parameters of the accelerations (in their three axes) collected on the wrists and one leg were used—a total of nine variables (32,796 data points). Table 9 presents the interaction history. Iterations stopped because the maximum number of iterations was performed. The maximum absolute coordinate change for any centre is 0.547, and the current iteration is 10. The minimum distance between the initial centres is 575.296. Table 10 shows the distances between the final cluster of activity centres, and Table 11 presents the number of cases in each cluster.

**Table 7.** Verification process.

Subject	Task	Time	Wrist (Dominant)			Wrist			Leg			Case N.	Cluster	Distance	Test
1	Masonry	10:40:18	284	117	212	131	123	113	92	40	62	942	Masonry	268.6488	TRUE
1	Masonry	10:40:19	50	66	99	227	110	164	60	119	96	943	Masonry	156.0831	TRUE
1	Masonry	10:40:20	67	63	99	69	65	180	141	135	90	944	Masonry	124.6410	TRUE
1	Masonry	10:40:21	112	83	6	69	80	165	143	135	39	945	Masonry	132.9037	TRUE
1	Masonry	10:40:22	41	59	55	121	93	57	11	55	31	946	Painting	137.2267	FALSE
1	Masonry	10:40:23	201	160	153	43	63	42	12	47	1	947	Roughcast	134.2535	FALSE

**Table 8.** Set-up of three clusters.

Output Created		
	Active Dataset	DataSet0
	Filter	<none>
Input	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	3644
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any clustering variable used.
		QUICK CLUSTER
		VAR00006-07-08-09-10-11-12-13-014
		/MISSING = LISTWISE
Syntax	Wrist (dominant) 3 VAR	/CRITERIA = CLUSTER(3) MXITER(10)
	Wrist (non-dominant) 3 VAR	CONVERGE(0) /METHOD =
	Leg (dominant) 3 VAR	KMEANS(ROUPDATE)
		/SAVE CLUSTER DISTANCE
		/PRINT INITIAL ANOVA CLUSTER DISTAN.

**Table 8.** *Cont.*

Output Created		
Resources	Processor Time	00:00:00.44
	Elapsed Time	00:00:00.00
Variables Created or Modified	Workspace Required	1944 bytes
	QCL_1	Cluster Number of Case
	QCL_2	Distance of Case from its Classification Cluster Centre

**Table 9.** Interaction history.

Iteration	Change in Cluster Centres		
	Sawing	Screwing	Hammering
1	261.0570	345.3322	323.5139
2	58.5810	76.7062	55.8298
3	65.0758	25.0337	21.6352
4	14.4996	11.5637	8.7550
5	3.3059	6.6206	3.7269
6	0.5369	4.2438	2.0083
7	0.4353	2.3990	1.0646
8	0	1.2704	0.5940
9	0	0.7804	0.3616
10	0	0.8472	0.3929

**Table 10.** Distances between final cluster centres.

Cluster	Sawing	Screwing	Hammering
Sawing		260.6854	244.6953
Screwing	260.6854		108.0933
Hammering	244.6953	108.0933	

**Table 11.** Number of cases.

Number of Cases in Each Cluster		
Cluster	Sawing	1172
	Screwing	783
	Hammering	1689
Valid		3644
Missing		0

Each of the 3644 lines (activities identified in each second) is identified by a cluster. A small extraction of this information is shown in Table 12. Again, the true or false analysis was carried out to evaluate the accurate labelling. The multivariate analysis of Manual tools (Hammering, Sawing and Screwing) process and tasks indicated 2772 correct values in 3644, reaching an accuracy of 76.07%. In contrast, using just three axes of the dominant hand (10,932 data points), it achieved 76.23% accuracy.

Table 13 presents the set-up requirements for a non-hierarchical classification for the group containing the activities of Wearing PPE, Sitting, Standing still and Walking. To obtain the four clusters of activities, data of the wrists and one leg were used as nine variables (23,562 data points).



**Table 12.** Validation process.

Subject	Task	Time	Wrist (Dominant)			Wrist			Leg			Case N.	Cluster	Distance	Test
2	Sawing	14:34:47	262	25	46	0	4	0	0	0	0	7	Sawing	290,162	TRUE
2	Sawing	14:34:48	171	36	35	0	1	0	0	0	0	8	Sawing	1,086,854	TRUE
2	Sawing	14:34:49	85	222	152	0	0	0	0	0	0	9	Screwing	1,380,763	FALSE
2	Sawing	14:34:50	43	91	314	0	0	0	0	0	0	10	Screwing	2,154,279	FALSE
2	Sawing	14:34:51	83	25	81	0	0	0	0	0	0	11	Hammering	821,257	FALSE
2	Sawing	14:34:52	337	72	32	0	0	0	0	1	1	12	Sawing	638,884	TRUE

**Table 13.** Set-up of four clusters.

Output Created		
	Active Dataset	DataSet0
Input	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	2618
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any clustering variable used. QUICK CLUSTER VAR00006-07-08-09-10-11-12-13-014 /MISSING = LISTWISE /CRITERIA = CLUSTER(4) MXITER(10) CONVERGE(0) /METHOD = KMEANS(NOUPDATE) /SAVE CLUSTER DISTANCE /PRINT INITIAL ANOVA CLUSTER DISTAN.
Syntax	Wrist (dominant) 3 VAR	
	Wrist (non-dominant) 3 VAR	
	Leg (dominant) 3 VAR	
Resources	Processor Time	00:00:00.37
	Elapsed Time	00:00:00.00
	Workspace Required	2288 bytes
Variables Created or Modified	QCL_1	Cluster Number of Case
	QCL_2	Distance of Case from its Classification Cluster Centre

Table 14 presents the interaction history that stopped because the maximum number of iterations was performed. The minimum distance found between the initial centres is 531.495. With ten current iterations, the maximum absolute coordinate change for any centre is 3.637. Table 15 presents the distances between the final cluster of activity centres. Table 16 shows the number of cases in each cluster.

**Table 14.** Interaction history.

Iteration	Change in Cluster Centres			
	Standing Still	Walking	Wearing PPE	Sitting
1	253.1632	271.7627	253.8942	247.4363
2	34.6668	23.8132	28.9162	41.9111
3	15.3285	11.9069	30.5345	16.2089
4	12.8381	4.6949	37.3199	9.3450
5	11.1022	6.0636	29.6576	8.6092
6	9.2294	3.8355	19.1764	5.9783
7	7.2804	3.4810	15.1276	5.1283
8	7.4817	1.9499	12.9699	4.6997
9	6.0755	0.8473	10.0764	5.9705
10	3.6753	1.3617	6.6054	5.3191

**Table 15.** Distances between final cluster centres.

Cluster	Standing Still	Walking	Wearing PPE	Sitting
Standing still		272.6942	185.9325	362.6586
Walking	272.6942		190.9127	162.3144
Wearing PPE	185.9325	190.9127		228.9966
Sitting	362.6586	162.3144	228.9966	

**Table 16.** Number of cases.

Number of Cases in Each Cluster		
Cluster	Standing still	763
	Walking	742
	Wearing PPE	725
	Sitting	388
Valid		2618
Missing		0

A small extraction of the clustering information regarding the processing of the 2618 lines (activities identified in each second) is shown in Table 17. The multivariate analysis of the activities of Wearing PPE, Sitting, Standing still and Walking indicated 1249 correct values in 2618, reaching an accuracy of 47.71%. Finally, an accuracy of 46.60% was achieved by clustering the data from three axes of the dominant hand (9138 data points).

**Table 17.** Validation process.

Subject	Task	Time	Wrist (Dominant)			Wrist			Leg			Case N.	Cluster	Distance	Test
4	Walking	15:29:51	53	39	145	175	27	193	19	33	47	930	Wearing	1,636,731	FALSE
4	Walking	15:29:52	110	68	286	96	32	41	25	77	60	931	Wearing	2,104,327	FALSE
4	Walking	15:29:53	74	46	100	77	76	140	97	130	50	932	Walking	896,969	TRUE
4	Walking	15:29:54	124	48	73	22	99	208	115	175	28	933	Walking	1,569,528	TRUE
4	Walking	15:29:55	112	57	72	71	164	245	103	197	29	934	Walking	1,987,402	TRUE
4	Walking	15:29:56	58	126	233	68	188	302	104	168	38	935	Sitting	2,836,098	FALSE

Tables 18 and 19 present a summary of all the analyses. The process Manual tools with the three activities (Hammering, Sawing and Screwing) achieved higher accuracy in both situations—Wrists and Leg (76.07%) and Wrist-dominant (76.23%). Additionally, it was the only case of the highest accuracy, only clustering the Wrist-dominant data. As seen, the group of two processes and three activities, “Free-hand performing (Masonry) + Manual tools (Painting, Roughcasting)”, achieved an accuracy of 60.90% (Wrists and Leg) and (32.50%). In this case, the analysis by using only the wrist-dominant data decreased the accuracy by almost a half. Finally, the lowest accuracy was identified in the group of two processes and four activities—“Do not operate value (Wearing PPE, Sitting, Standing still) + Walking (Walking)”—47.41% and 46.60%, respectively, for Wrists and Leg, and Wrist-dominant data. In this case, a slight difference was noted.

In the “Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting)” group, when only the data of the dominant wrist was considered, a high increase in the maximum absolute coordinate change for any centre was observed. Additionally, the distances between the final cluster centres decreased significantly. This was not verified in the other two cases, which maintained approximate values in both scenarios. Forward in the next section, a summary analysis will be performed.

**Table 18.** Classification results summary.

Data		Free-Hand Performing Plus Manual Tools	Manual Tools	Do Not Operate Value Plus Walking	Average	Median
Accuracy	Wrists and Leg	60.90%	76.07%	47.41%	61.46%	60.90%
	Wrist (dominant)	32.50%	76.23%	46.60%	51.78%	46.60%
Acceleration data points	Difference	>28.4%	<0.16%	>0.81%		
	Wrists and Leg	27,414	32,796	23,562		
The maximum absolute coordinate change for any centre	Wrist (dominant)	9138	10,932	7854		
	Wrists and Leg	0.836	0.547	3.637		
The minimum distance between initial centres	Wrists and Leg	584.024	575.296	531.495		

**Table 19.** Clustering results summary.

Data		Free-Hand Performing Plus Manual Tools	Manual Tools	Do Not Operate Value Plus Walking
Distances between final cluster centres	i	159.1544	260.6854	272.6942
	ii	283.4235	244.6953	185.9325
	iii	233.6170	108.0933	362.6586
	iv			190.9127
	v			162.3144
	vi			228.9966
	Average	225.3983	204.4913	233.9182
The maximum absolute coordinate change for any centre	Wrist (dominant)	9.536	1.041	9.544
The minimum distance between initial centres	Wrist (dominant)	512.347	512.347	481.594
Distances between final cluster centres	i	131.3473	241.3922	163.2217
	ii	205.7065	107.7671	192.3734
	iii	128.8105	257.2948	271.5576
	iv			120.2651
	v			111.9096
	vi			195.5329
	Average	155.2882	202.1514	175.8099

#### 4.4. Classification and Clustering Cross-Analysis

Figure 14 illustrates the accuracy achieved by the machine-learning process and the multivariate statistical analysis. The classifications performed through machine learning reached high precision in all three cases. Multivariate statistical analysis evidenced moderate accuracy. Subsequently, an analysis is developed to highlight the different classification accuracy results when using the three collection points and is carried out only with the wrist-dominant data. The objective is to explain why there is a loss of approximately 50% of accuracy in the first group, while in another case (Manual tools), there is a subtle increase in accuracy, and in the last group, only a difference of less than 1% is observed. Finally, based on the results and the analyses, it is possible to put forward an overall evaluation of the machine-learning methods and multivariate statistical analysis (see Figure 15). The purpose of these classifiers is to avoid manual data processing, as in a real-life construction situation, the large volume of data would result in extensive manual work.

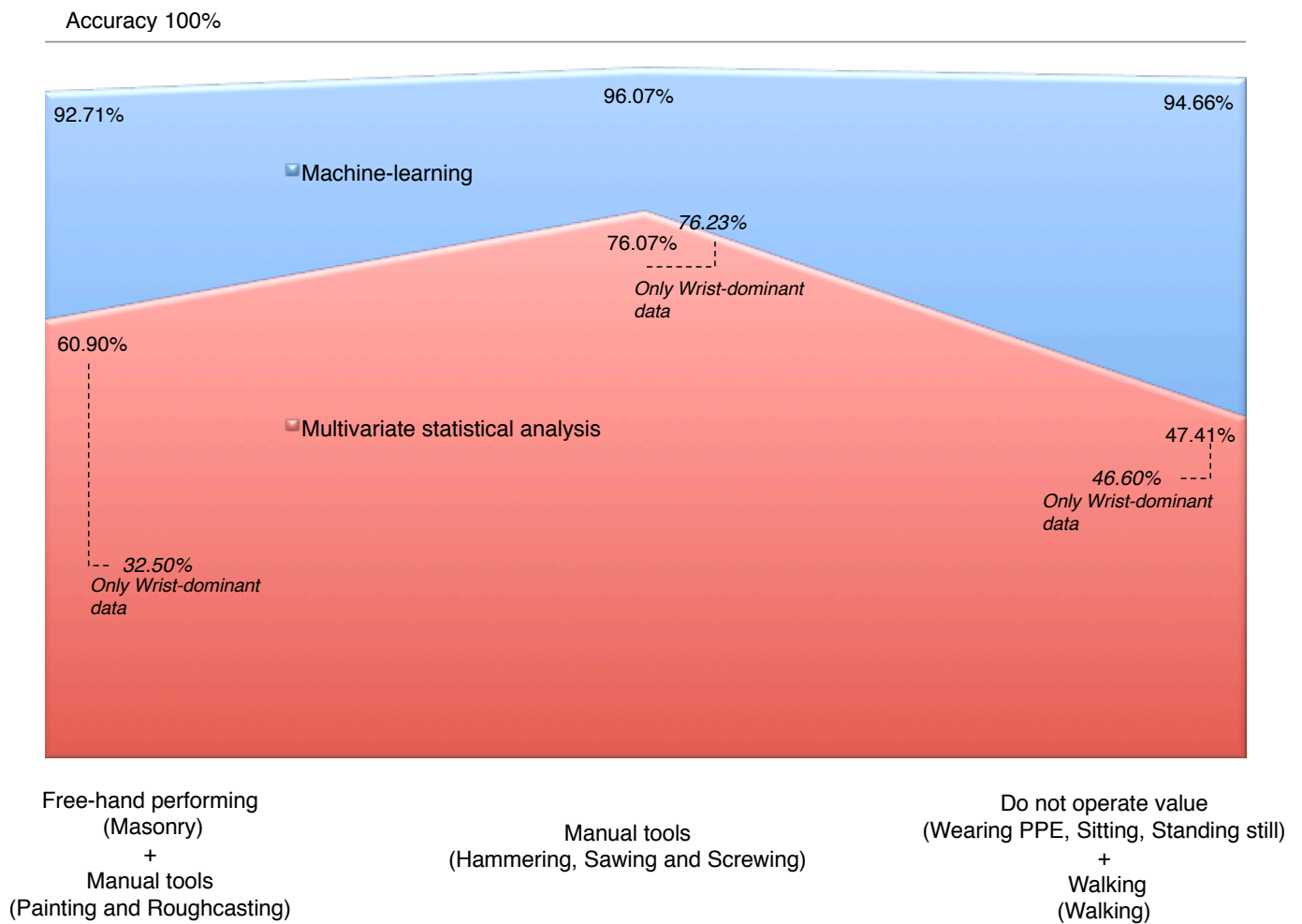


Figure 14. Machine learning vs. Multivariate statistical analysis.

	Pre-labelling	Features (processed)	Accuracy	Computational demand	Expert knowledge	Training sets to process	Standalone algorithm
Machine Learning	yes	235 (initially) 150 (filtered)	very high 94%	very high	high	yes	yes
Multivariate Statistical Analysis	yes	9 (3x 3-axis) 3 (1x 3-axis)	moderate 60%	low	low	no	no

Figure 15. Comparative evaluation.

It can be concluded that the multivariate statistical analysis method alone is not able to label actions. However, multivariate analysis can speed up the labelling work, since a preliminary process can seek to cluster the data and facilitate their visual interpretation. The multivariate analysis method is more straightforward than machine learning and can

achieve a moderate accuracy with fewer features to vectorise, demanding lower expert knowledge and computational capacity. The enormous potential of machine learning is in creating algorithms that, once able to interpret an activity (based on acceleration), can perform this task without the need for pre-labelling or training sets. The idealised format of an activity circuit can assist in the algorithms' calibration, since a new individual can be monitored in a known and pre-established sequence of activities/actions.

## 5. Conclusions

The dynamic circuit proposed in this paper makes EPM laboratory experimentation more similar to the on-site reality. The option of grouping the activities with different motion characteristics proved essential for the analysis, since it was demonstrated that having heterogeneous motions/acceleration activities hampers the classification process. Future research in the field of EPM and activity classification should observe this practice of clustering activities with distinct motion characteristics. Moreover, this is an accurate picture of the work developed for the craft workers on site. The activities' classifications and their grouping over a process analysis allow a deep understanding of the motion characteristics. However, process modelling analysis can provide better performance evaluation.

The experiment conducted to test the circuit feasibility deploys electronic monitoring, using wearable devices (IMUs) to collect motion acceleration of wrists and the dominant leg. Activities with multiple motions characteristics, such as free-hand performing (e.g., masonry), walking and do not operate value (e.g., Wearing PPE and Sitting), require more motion analysis data points, such as wrists and legs. On the other hand, processes conducted with Manual tools (e.g., painting, roughcasting, hammering, sawing and screwing) have prominent dominant-hand motion characteristics that are easily detected with just one wearable. In summary, processing the data with two approaches (i.e., machine learning and MSA, in a laboratory circuit with six subjects using three activity groups resulted in the following:

- The "free-hand performing (Masonry) plus two manual tools (Painting and Roughcasting)" group achieved a 92.71% accuracy for the machine-learning approach and 60.09% for MSA when using three IMUs (both wrists and one at the dominant leg). When using only one IMU (only wrist-dominant data), MSA reached 32.50% accuracy;
- The "manual tools (Hammering, Sawing and Screwing)" group achieved a 96.07% accuracy for the machine-learning approach and 76.07% for MSA when using three IMUs (both wrists and one at the dominant leg). When using only one IMU (only wrist-dominant data), MSA reached 76.23% accuracy;
- Finally, the "do not operate value (Wearing PPE, Sitting, Standing still) and walking (Walking)" group achieved a 94.66% accuracy for the machine-learning approach and 47.41% for MSA when using three IMUs (both wrists and one at the dominant leg). When using only one IMU (only wrist-dominant data), MSA reached 46.60% accuracy.

In practice, the approach of classifying workforce activities is to better understand and map the on-site processes. Proper activity classification is crucial for modelling the construction process and applying lean concepts and unnecessary motion elimination. Task data analysis can quantify the time spent by the worker using a manual tool, walking-travelling or carrying elements, for instance. These data can be used to implement improvements, for example, providing electric tools or bench stations and reorganising the site stock to avoid long walks to collect elements and accessories.

The main contribution of this research is to establish and test an EPM laboratory circuit-based simulation that introduces a way to develop, test and improve in-house EPM solutions for deployment on site. The laboratory circuit is the appropriate testbed environment to develop data processing approaches, for example, mixing methodologies to improve the accuracy and outcome lead time. Additionally, in the laboratory, multiple wearable devices and other technologies (e.g., filming) can be combined in different ways, changing data collection points and assessing the impact of these changes on the solutions' autonomy, scalability and user comfort.



It is expected that the development of similar circuits in other locations will enable comparisons with the results presented in this paper. Further research will focus on setting a larger circuit, adding activities such as inspection duties, electric tools use and machine operations. Additionally, other mixed approaches to electronic performance monitoring will be tested using images, sound and geolocation. Finally, developing faster and more accurate data processing algorithms is a critical goal for this type of solution to be deployed on site.

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