# Fall Detection: Sensor Data for Classification


Vinícius A. de Albuquerque, Bruno J. T. Fernandes
Polytechnic School of Pernambuco - POLI
University of Pernambuco - UPE
Email: {vaa,bjtf}@ecomp.poli.br



***Abstract*—To fall represents a major risk to the health of elderly people. Combining Machine Learning techniques with data from sensors, automatic systems that detect and report falls can be created. This strategy would help to prevent greater damages in these people's health. So this work aims to compare the performance of different classifiers in the fall detection problem. We apply the SisFall dataset, which provides sensors measurements from people's daily-living activities and falls. The results show that some of the tested classifiers are efficient in this task, reaching an accuracy of 99.74% and 99.6325%.**


## I. Introduction

Falling is considered to be a major public health problem for the elderly people since it can bring severe consequences, such as serious injures or even death [1]. Even when no grave physical injure occurs, the resultant fear of falling and self-imposed limitations in mobility may be contributing for nursing homes admissions [2]. Every year, one in three persons older than 65 years old is estimated to fall [3]. And falling once doubles the chance of falling again [4].

In addition to all of that, not only the fall itself represents a danger to the health of people, the damages of falling can be amplified by the event called "long lie", which consists in remaining down on the floor for one hour or more after a fall [3]. The long lie is a marker of weakness, illness and social isolation and is associated with high mortality rates among the elderly [5]. Falls are still likely to happen as an individual gets older and to prevent greater damages , they have to be noticed and reported fast [3].

To detect a fall, personal emergency response systems (PERS) are used. The most common one, the push-button, is not always satisfactory because due to a loss of consciousness or people not activating their PERS even when they have the ability to do so, falls are not reported [6].

To prevent that, automatic systems are being developed. There are two major types of approaches to automatic fall detection devices. Wearables (sensors), and ambient-based , such as cameras (vision-based) [7].

The experiment done in this work focus on the wearable approach, using the accelerometer sensor data available in the dataset and some classifiers to detect when an individual falls more accurately. And the results using this line of thought show that some of the tested classifiers achieve a high rate of accuracy, reaching rates of 99.7455%, 99.6325% of accuracy. By doing that, we hope to develop means to help people in need so they suffer as little as possible the consequences of this type of accident.

This paper is organized as follows: in Section 2 we make a brief review about a few related work that influenced this article in some way; then, the next Section, 3, is focused on showing the model of the processes used to achieve the results; the Section 4 the whole experimentation, since the dataset until the results and discussions; Section 5 we conclude our article and talk about future works.

## II. Related Work

The majority of the works done in the field of Fall Detection uses sensors to identify a fall. Bianchi et al. [8] use a barometric pressure sensor, an accelerometer and a heuristically trained decision tree classifier to identify possible falls. The experiment uses 20 young healthy volunteers. They reach 96.9%, 97.5%, and 96.5% in accuracy, sensitivity and specificity, respectively.

Kang et al. propose another approach in [9] that achieves an accuracy of 96%. Information about They use a single waist-mounted triaxial accelerometer and a hierarchical binary tree to classify a fall considering 5 young healthy subjects. There is no information about sensitivity or specificity.

In the same context, Karantonis et al. [10] also propose using data provided by a waist-mounted triaxial accelerometer unit in a real-time movement classifier using embedded intelligence. The experiments consist on 12 different tasks of daily life activities. They detected possible falls with an accuracy of 95.6%. No information about sensitivity and specificity were given.

Noury et al. [11] discuss about many researches and systems already done in the field of fall detection. They propose the use of Sensibility(also called Recall) and Specificity as evaluation measures not only because to create a pattern for future comparison but also because it is important to be aware with the results of True Positives(TP), False Negatives(FN), False Positives(FP) and True Negatives(TN).

There are also studies of fall detection using another approaches, such as vision-based, but since this work focus on the sensors, they were not discussed in this section.

## III. Fall Detection Model

This section is focused on explaining what is necessary to achieve the results obtained in this work. The Figure 1 shows a diagram of our model.

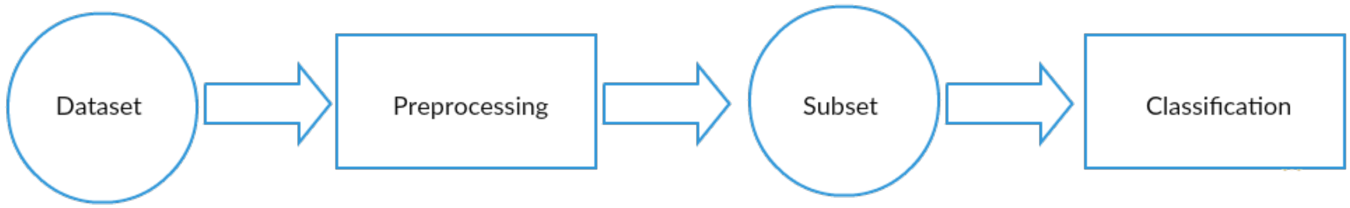


Fig. 1. Model of Fall Detection

### A. Preprocessing

The information extracted of the dataset gives us many types of activities divided in two big groups. One being a group that contains all the activities of the subjects when they don't fall, and the other group being the one containing all the activities where the subjects do fall. It was not important, at the moment, for us to know which type of ADL or which type of fall happened, so, for this experiment, two classes are defined: fall and no_fall.

As it is mentioned before, for exception of one individual, elderly people did not do fall experiments in the SisFall dataset [7]. Therefore, by means of not unbalancing the experiment, only tasks done by young adults are considered.

Due to the great amount of information for each experiment in the dataset, a preprocessing is made so the data passed to the classifiers is smaller, which lowers time processing needed to train and evaluate the data.

Besides that, only one of the accelerometers was chosen. Each file of the dataset has thousands of sensor values (consists of x,y and z axis information at that exact moment) during the activity. Seeking making the data even smaller, only 102 attributes were selected of each file. In this case, each axis is considered to be an attribute. That means, for each group of (x,y,z), three attributes are collected.

The Algorithm 1 was used to select the points of the files. This algorithm consists on getting the $K$ groups of (x,y,z) by dividing the total of groups in the file by $K$, we are going to call that value as $D$. Then, to form the subset we want, we get the triaxis (x,y,z) value for every line which its index divided by $D$ has the remainder equals to zero.

**Algorithm 1** Pseudocode for triaxis (x,y,z) selection

**Require:** $n \geq 0 \vee x \neq 0$
**Ensure:** $y = x^n$
  $y \Leftarrow 1$
  $nATT \leftarrow 102$
  **while** $file \leftarrow files$ **do**
    $attributesCounter \leftarrow 0$
    $lineCounter \leftarrow 0$
    $divider \leftarrow (numberOfLinesInFile/nATT) * 3$
    **while** $currentLine \leftarrow linesOfFile$ **do**
      **if** $lineCounter$ lessThan $nATT$ **then**
        **if** $lineCounter$ mod $divider$ equalTo 0 **then**
          GET 3 AXIS
          $attributesCounter \leftarrow attributesCounter + 3$
        **end if**
        $lineCounter \leftarrow lineCounter + 1$
      **else**
        $break$
      **end if**
    **end while**
    if a file had less than nATT attributes, null values were added.
  **end while**

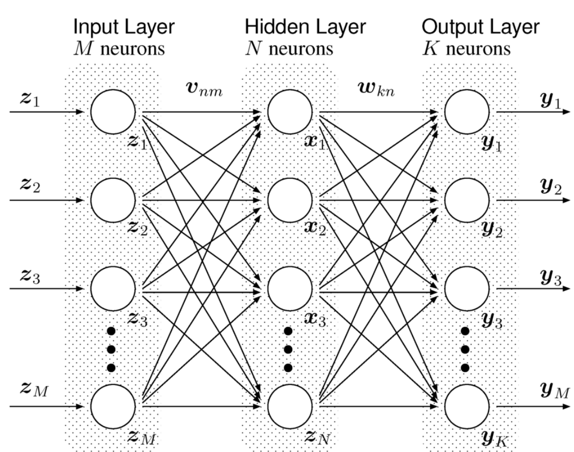


Fig. 2. MLP Example

### B. Classification

The following classifiers were the ones chosen for the experimentation in this work:

*1) Classifiers:*

- Multilayer Perceptron (MLP)
  A system of interconnected neurons that represents a nonlinear mapping between an input vector and an output vector [12]. An example of the structure of a MLP can be seen in the Figure 2
- Decision Table
  It is a tabular representation used to describe and analyze decision situations, where the state of a number of conditions jointly determines the execu- whereas the actions correspond to the outcome classes tion of a set of actions [13].
  A simple example of a decision table can be seen in

Figure 3

| **Conditions** | **R1** | **R2** | **R3** |
|---|---|---|---|
| Withdrawal Amount <= Balance | T | F | F |
| Credit granted | - | T | F |
| **Actions** | | | |
| Withdrawal granted | T | T | F |

Fig. 3. Decision Table Example

- Support Vector Machine (SVM) It is a machine learning system that uses a hypothesis space of linear functions in a high dimensional feature space. It is trained with optimization algorithms that implement a learning bias derived from statistical learning theory [14].

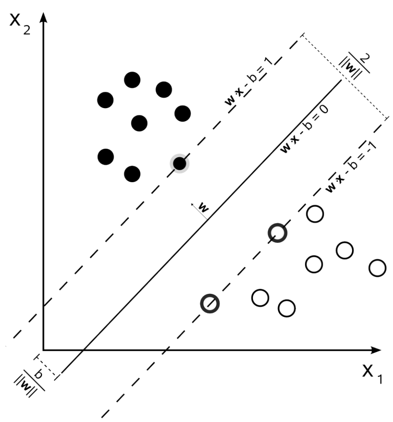


Fig. 4. SVM Example

- Random Forest
  It is a classifier consisting of a collection of tree-structured classifiers $\{h(x, \Theta_k), k = 1, ...\}$ where the $\{\Theta_k\}$ are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x [15]. An example of the structure of a Random Forest is shown on Figure 5.

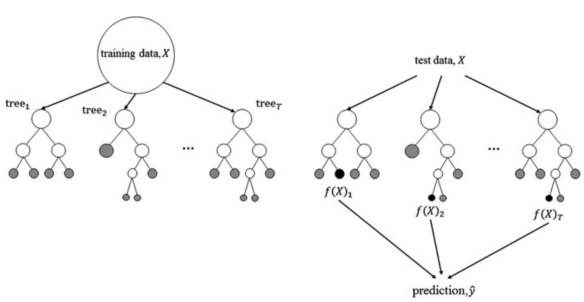


Fig. 5. Random Forest Example

- Bayesian Network (Bayes Net)
  Directed acyclic graphs that allow efficient and effective representation of the joint probability distribution over a set of random variables. Where each vertex in the graph represents a random variable, and the edges represent direct correlations between the variables [16]. A simple example of a Bayes Net is showed on Figure 6.

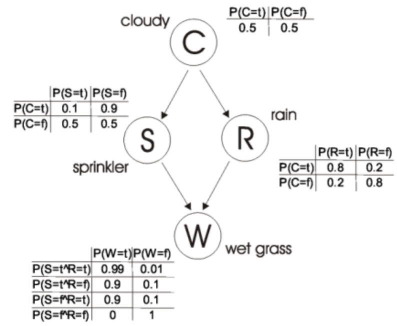


Fig. 6. Bayes Net Example

## IV. Experimentation

This work makes use of the software Waikato Environment for Knowledge Analysis (WEKA) [17], a data mining software that contains machine learning algorithms. The version which the tests are executed is the WEKA 3.8.1.

### A. The Dataset

Even with the promising growth in the field of fall and movement wearable devices, there aren't many public available information on this type of research. So, [7] proposes a public dataset of falls and activities of daily living (ADL). It consists of 4510 files where each file has the measurements of the three axis (X, Y and Z) of 3 different sensors, two accelerometers and one gyroscope of a single activity. This dataset has different types of ADL and falls performed by young adults (aged between 19 and 30) and seniors (aged between 60 and 75) [7].

The experiments to collect the data of this dataset were made with a device containing the sensors fixed on the waist of the subjects.

The Figure 7 shows a few examples of what can be found in the SisFall Dataset.


Fig. 7. Dataset activities example.

The specifications of the sensors used in this are:

- Accelerometers

- ADXL345
  - Resolution: $13 bits$
  - Range: $+-16g$
- MMA8451Q
  - Resolution: $14 bits$
  - Range: $+-18g$

- Gyroscopes
  - ITG3200
    - Resolution: $16 bits$
    - Range: $+-2000\infty/s$

All of them working at a frequency sample of 200Hz.

It is important to say that there were activities that were not performed by the elderly group due to personal impairments or medical recommendation.

Some of the types of falls and ADLs present in this dataset are:

- ADLs
  - Walking slowly
  - Jogging slowly
  - Quickly sit in a half height chair, wait a moment, and up quickly
  - Gently jump without falling (trying to reach a high object)
- Falls
  - Fall forward while walking caused by a slip
  - Fall forward when trying to get up
  - Fall backward when trying to sit down
  - Lateral fall when trying to get up

### B. Classifiers Parametrization

To obtain the results that will be presented later in this paper, the classifiers use the following configurations:

- MLP
  The learning rate were changed between 0.1 and 0.5. In the next step the number of hidden layers was modified varying 1 to 5. Finally the activation function had allow tests with different values (Sigmoid, hyperbolic tan and linear function).
  - Activation Function: Sigmoid
  - Learning Rate: 0.2
  - Hidden Layers: 2
  - Epochs: 500
- Decision Table
  - Search: Best First
  - Search Termination: 5
  - Direction: Forward
- SVM
  Only eps and type of the kernel was changed in the tests. The kernels utilized were: RBF, linear, polynomial and sigmoid.
  - Kernel: Polynomial
  - Cost: 1
  - Eps: 0.7
  - Coef: 1.0
  - Gamma: 0.0
- Random Forest
  In the random forest classifier, the parameters tested were the number of interactions and max depth.
  - Number of Iterations: 100
  - Max Depth: 0 (unlimited)
  - Seed: 1
- Bayes Net
  - Estimator: Simple Estimator
  - Search Algorithm: Bayes
  - Initializing as Naive Bayes
  - Max Number of Parents: 1

### C. Evaluation

For the validation of the results, we chose the K-Fold Cross-Validation. This method randomly splits the provided dataset into K subsets, also called folds. Then the selected algorithm is trained and tested K times. Thus, each time that this algorithm is trained, one of the K folds is selected to be the test subset. So, the accuracy of this method is given by the overall number of correct classifications divided by the number of instances in the dataset [18].

The Figure 8 shows an example of a K-fold Cross-Validation where the K, the number of folds, is equal to 5.

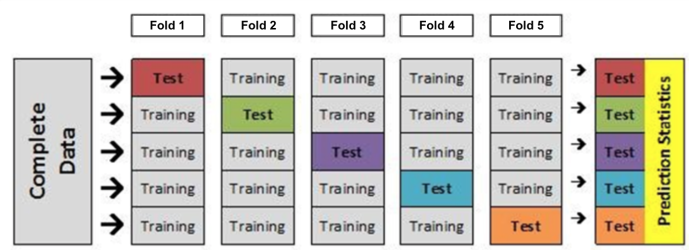


Fig. 8. Cross-Validation Example

Besides the accuracy, the evaluation method also gives us the confusion matrix. The confusion matrices show the amount of fall and ADLs correctly and wrongly classifications. That information shows us the True Positive, False Positive, True Negative and False Negative. They are defined as such:

- True Positive (TP): a fall occurs, the device correctly detects it
- False Positive (FP): the device announces a fall, but it did not occur
- True Negative (TN): a fall did not occur and the device did not announce a fall
- False Negative (FN): a fall occurs but the device does not detect it

Following this method of evaluation, to be considered an acceptable solution, the classifier must have high amounts of TP and low amounts of FN. That means, the system cannot not identify a fall. It can be inconvenient to classify a fall when it did not happen but to not report a fall when it did happen is what we have to try to minimize as much as it is possible.

To be considered a good solution, it has not only to have what was discussed in the last paragraph but also high rates of accuracy.

### *D. Results and Discussions*

As we can also see in Fig 7. The Table I shows the results of the experiments, evaluated by Accuracy, Precision, Recall and Specificity. The classifier that reached the highest rates in accuracy was the Random Forest. We observe that it reached a 99.7455% of accuracy and a low number of FN, 6. That means, in over three thousands tests, only 6 falls happened and were not classified as such for this classifier.

In the confusion matrices - Table III to Table VI - it can be observed the numbers of TP, FP, TN and FN. Therefore, we can observe how many of each class was correctly and wrongly classified. Knowing that, we can observe that the MLP had the lowest FN rate. That means, it was the best one on detecting the actual fall. That is a relevant information because, even though the MLP can give you the inconvenience of reporting a fall when it did not happen more times than the Random Forest, it has a lower probability of not reporting a fall when it actually happen.

TABLE I
CLASSIFICATION RESULTS TABLE

| Classifier | Accuracy | Precision | Recall | Specificity |
|---|---|---|---|---|
| RandomForest | 99.7455% | 0.998 | 0.996 | 0.998 |
| MLP | 99.6325% | 0.994 | 0.997 | 0.995 |
| SVM | 98.4733% | 0.976 | 0.993 | 0.976 |
| DecisionTable | 99.2932% | 0.994 | 0.991 | 0.994 |
| BayesNet | 98.6995% | 0.985 | 0.987 | 0.986 |

TABLE II
CONFUSION MATRIX - RANDOM FOREST

| | | CLASSIFIED | |
|---|---|---|---|
| | | FALL | NO_FALL |
| ACTUAL | FALL | 1717 | 6 |
| | NO_FALL | 3 | 1811 |

TABLE III
CONFUSION MATRIX - MLP

| | | CLASSIFIED | |
|---|---|---|---|
| | | FALL | NO_FALL |
| ACTUAL | FALL | 1719 | 4 |
| | NO_FALL | 9 | 1805 |

TABLE IV
CONFUSION MATRIX - SVM

| | | CLASSIFIED | |
|---|---|---|---|
| | | FALL | NO_FALL |
| ACTUAL | FALL | 1717 | 6 |
| | NO_FALL | 10 | 1804 |

TABLE V
CONFUSION MATRIX - DECISION TABLE

| | | CLASSIFIED | |
|---|---|---|---|
| | | FALL | NO_FALL |
| ACTUAL | FALL | 1708 | 15 |
| | NO_FALL | 10 | 1804 |

TABLE VI
CONFUSION MATRIX - BAYES NET

| | | CLASSIFIED | |
|---|---|---|---|
| | | FALL | NO_FALL |
| ACTUAL | FALL | 1702 | 21 |
| | NO_FALL | 25 | 1789 |

## V. CONCLUSION AND FUTURE WORKS

Is has already been discussed here in this paper that the faster a fall is reported, the higher is the probability of a full recovery. Therefore, making fall detection a very important field of study. For that purpose, we made comparisons of which methods of classifications would have a good response for that goal. We achieved the conclusion that the Random Forest and the MLP had the best results, having accuracy of 99.7455% and 99.6325% respectively. Even though the MLP had a lower rate of accuracy, it had a lower amount of FN, which means that less falls happened without being reported.

In this paper we had the limitation of not having the data for falls in elderly people which is the main target for this kind of research, so we cannot say for sure that the accuracy that we obtained here in this work will be maintained if we applied this work to these individuals.

We hope that this research brings more awareness about this serious issue. Bringing more attention to it, we can develop even more in better solutions and, consequently, help the people that need a special care.

To make this paper more complete, we intend to do an addition of more detailed information about the sensors used in the dataset. Showing the signals of the sensors for fall and for ADL events can facilitate a discussion where better conclusions about the problem can be made.

After that, the next step of this work is to apply the results of this experiment and apply it in a device. The first option is smartphones. Besides the fact that their use is growing each day, they also include a robust hardware, powerful processor and the are economically affordable [7].

Not only it would be the device of identification of a fall but, since it also is a tool of communication, it would also be the device responsible for reporting the accident.

Another step to be taken is reduce even more the amount of points selected of the files so the classification would be even faster and for the processing power needed for that task be even smaller whilst trying to keep high rates of accuracy. For that, we can not only alter the parameters of the algorithm defined here (Algorithm 1) but also define another strategy for feature extraction.

## REFERENCES


[1] Z. Zhang, C. Conly, and V. Athitsos, "A survey on vision-based fall detection," in *Proceedings of the 8th ACM International Conference on PErvasive Technologies Related to Assistive Environments*. ACM, 2015, p. 46.

[2] J. M. Hausdorff, D. A. Rios, and H. K. Edelberg, "Gait variability and fall risk in community-living older adults: a 1-year prospective study," *Archives of physical medicine and rehabilitation*, vol. 82, no. 8, pp. 1050–1056, 2001.

[3] S. Chaudhuri, H. Thompson, and G. Demiris, "Fall detection devices and their use with older adults: a systematic review," *Journal of geriatric physical therapy (2001)*, vol. 37, no. 4, p. 178, 2014.

[4] J. L. O'Loughlin, Y. Robitaille, J.-F. Boivin, and S. Suissa, "Incidence of and risk factors for falls and injurious falls among the community-dwelling elderly," *American journal of epidemiology*, vol. 137, no. 3, pp. 342–354, 1993.

[5] S. R. Lord, C. Sherrington, H. B. Menz, and J. C. Close, *Falls in older people: risk factors and strategies for prevention*. Cambridge University Press, 2007.

[6] A. Bourke, J. Obrien, and G. Lyons, "Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm," *Gait & posture*, vol. 26, no. 2, pp. 194–199, 2007.

[7] A. Sucerquia, J. D. López, and J. F. Vargas-Bonilla, "Sisfall: a fall and movement dataset," *Sensors*, vol. 17, no. 1, p. 198, 2017.

[8] F. Bianchi, S. J. Redmond, M. R. Narayanan, S. Cerutti, and N. H. Lovell, "Barometric pressure and triaxial accelerometry-based falls event detection," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 6, pp. 619–627, 2010.

[9] D. W. Kang, J. S. Choi, J. W. Lee, S. C. Chung, S. J. Park, and G. R. Tack, "Real-time elderly activity monitoring system based on a tri-axial accelerometer," *Disability and Rehabilitation: Assistive Technology*, vol. 5, no. 4, pp. 247–253, 2010.

[10] D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, and B. G. Celler, "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring," *IEEE transactions on information technology in biomedicine*, vol. 10, no. 1, pp. 156–167, 2006.

[11] N. Noury, A. Fleury, P. Rumeau, A. Bourke, G. Laighin, V. Rialle, and J. Lundy, "Fall detection-principles and methods," in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*. IEEE, 2007, pp. 1663–1666.

[12] M. W. Gardner and S. Dorling, "Artificial neural networks (the multilayer perceptron)a review of applications in the atmospheric sciences," *Atmospheric environment*, vol. 32, no. 14, pp. 2627–2636, 1998.

[13] B. Baesens, R. Setiono, C. Mues, and J. Vanthienen, "Using neural network rule extraction and decision tables for credit-risk evaluation," *Management science*, vol. 49, no. 3, pp. 312–329, 2003.

[14] P. C. Deka *et al.*, "Support vector machine applications in the field of hydrology: a review," *Applied Soft Computing*, vol. 19, pp. 372–386, 2014.

[15] L. Breiman, "Random forests," *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.

[16] N. Friedman, D. Geiger, and M. Goldszmidt, "Bayesian network classifiers," *Machine learning*, vol. 29, no. 2-3, pp. 131–163, 1997.

[17] G. Holmes, A. Donkin, and I. H. Witten, "Weka: A machine learning workbench," in *Intelligent Information Systems, 1994. Proceedings of the 1994 Second Australian and New Zealand Conference on*. IEEE, 1994, pp. 357–361.

[18] R. Kohavi *et al.*, "A study of cross-validation and bootstrap for accuracy estimation and model selection," in *Ijcai*, vol. 14, no. 2. Stanford, CA, 1995, pp. 1137–1145.

POLI
ESCOLA POLITÉCNICA
DE PERNAMBUCO

## MONOGRAFIA DE FINAL DE CURSO

**Avaliação Final (para o presidente da banca)***

No dia 6 de Julho de 2017, às 16:00 horas, reuniu-se para deliberar a defesa da monografia de conclusão de curso do discente **VINICIUS ARAUJO DE ALBUQUERQUE**, orientado pelo professor **Bruno José Torres Fernandes**, sob título **Fall Detection: Sensor Data for Classification**, a banca composta pelos professores:

**Sérgio Campello Oliveira**
**Bruno José Torres Fernandes**

Após a apresentação da monografia e discussão entre os membros da Banca, a mesma foi considerada:

☒ Aprovada ☐ Aprovada com Restrições* ☐ Reprovada

e foi-lhe atribuída nota: 10,0 ( DEZ )

*(Obrigatório o preenchimento do campo abaixo com comentários para o autor)

O discente terá 07 dias para entrega da versão final da monografia a contar da data deste documento.

SÉRGIO CAMPELLO OLIVEIRA

BRUNO JOSÉ TORRES FERNANDES

* Este documento deverá ser encadernado juntamente com a monografia em versão final.