

# Risk situation detector for elderly people based on time series analysis

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**Abstract.** *Elderly people are more exposed to risk situations such as falls, sudden changes in vital signs and fainting. These situations become more common at this stage of life due to the natural decrease in the body's ability to coordinate movements adequately. Numerous studies have proposed health monitoring systems for this population group, but the use of these systems in real situations has shown that this approach is still insufficient to accurately differentiate a risk situation from person's daily activities. This project proposes the development of an effective and reliable health monitoring system for the elderly, through the continuous collection of time series extracted from movement sensors associated with vital signs. For this evaluation, an environment composed of a wearable device simulator, a mobile application simulator and a cloud system simulator was created, very close to the real scenario. This system, in its final model, presented an overall accuracy of 97%, showing that sensor fusion in a continuous data analysis architecture contributes to increasing the elderly risk detection capacity.*

**Resumo.** *Pessoas em idade avançada estão mais expostas a situações de risco como quedas, alterações bruscas em sinais vitais e desmaios. Estas situações se tornam mais comuns neste estágio da vida devido à diminuição natural da capacidade do corpo de coordenar os movimentos de forma adequada. Inúmeros estudos já propuseram sistemas de monitorização da saúde desta faixa populacional, porém o uso destes sistemas em situações reais mostrou que esta abordagem ainda é insuficiente para que uma situação de risco possa ser diferenciada com precisão de atividades da vida diária. Este projeto propõe o desenvolvimento de um sistema de monitoração da saúde de idosos eficaz e confiável, através da coleta contínua de séries temporais extraídas de sensores de movimento associados à sinais vitais. Para esta avaliação foi criado um ambiente composto por um simulador de dispositivo wearable, um simulador de aplicativo de celular e um simulador de sistema em nuvem, muito próximo ao cenário real. Este sistema, em seu modelo final, apresentou uma acurácia geral de 97%, mostrando que a fusão de sensores em uma arquitetura de análise contínua de dados contribui para o aumento da capacidade de detecção de risco em idosos.*

## **1. Problem Description**

Fall and risk situation detection in older adults using noninvasive devices still has crucial open research questions because we do not have a solution to solve real use cases in elderly real-life broadly. In recent years, we have experienced much research covering paramount open research questions, but almost all focus on solving parts of the problem.

These characteristics impose sensor technology restrictions to solve this problem [Anuradha, et al. 2020]. Currently, we can broadly classify available technologies in (i) environmental sensing-based systems, (ii) vision-based systems, and (iii) wearable sensor-based systems. Environmental and vision-based systems have a lot of disadvantages and because of that, a solution that pretends to perform accurate elderly fall detection in real-life scenarios, preserving user privacy, working full time independently of the environment, and increasing elderly acceptance must be based on a wearable sensor-based system [Warrington, Shortis e Whittaker 2021].

## **2. Research Motivation**

Machine learning (ML) has solved many problems that researchers worldwide have explored for many years, making it possible to detect falls, activities of daily living, and risk situations based on wearable devices, becoming the most promising technique to detect risky situations based on time-series analysis from wearable sensors. However, despite this apparent solution, we still have open research questions, like:

- Algorithms (ML or not) trained with datasets containing not real-life data
- Real-life datasets for training algorithms are complex to build
- Differences in behavior between elderlies in real-life use affect the accuracy

To address these problems, we proposed this doctoral Thesis, which consists of developing a risk situation detector based on machine learning for older people based on time series analysis combining motion and physiological sensors embedded in a wristwatch based on a model with the capacity to learn new data from the user, adapting it to the user environment.

## **3. Objectives and Research Contributions**

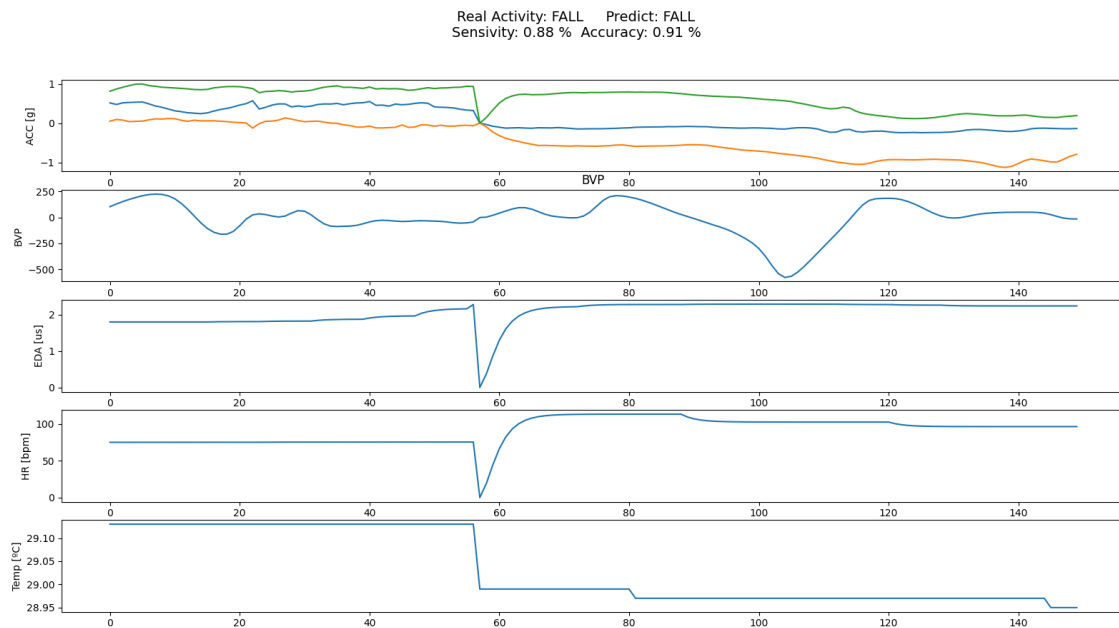
The proposed Thesis aims to develop an elderly-adapted risk situation detector based on machine learning, which will monitor risky situations in real time using subsequent techniques:

- Context analysis - Traditional fall detection algorithms are based on the advantage of detecting the peak signal in motion sensors when a fall occurs to detect it. To solve this problem, we propose using recurrent neural networks. This specific deep learning model considers a just data moment and the past and future data associated with one particular spatio-temporal point.

- Algorithm adapted to user - This research proposes an innovative algorithm based on the user-adaptation concept to solve the worst problem in wearable fall detection and activity classification, i.e., the high rate of false positives.
- Motion, environment, and physiological sensors fused - Motion sensors do not have the full information capacity to detect a fall, so we explore the idea of adding new sensor types to the decision-making process. Besides motion sensor abilities, physiological sensors provide information about the user's health, which can improve the results.

## 4. Results

To analyze the models proposed at this thesis, we used a real simulation of the model in practice to evaluate its performance with test data. This analysis is slightly different from the traditional approach, where data not known by the network (test data) is passed for direct classification. To do this, we sent the test data set through a stream at 32 Hz to be classified every 150 samples (4.68s), generating a new prediction. All predictions were tallied and analyzed and an example of the screen that shows the time series and predictions can be seen in **Figure 1**.



**Figure 1. Real time-series prediction system (Source: Author)**

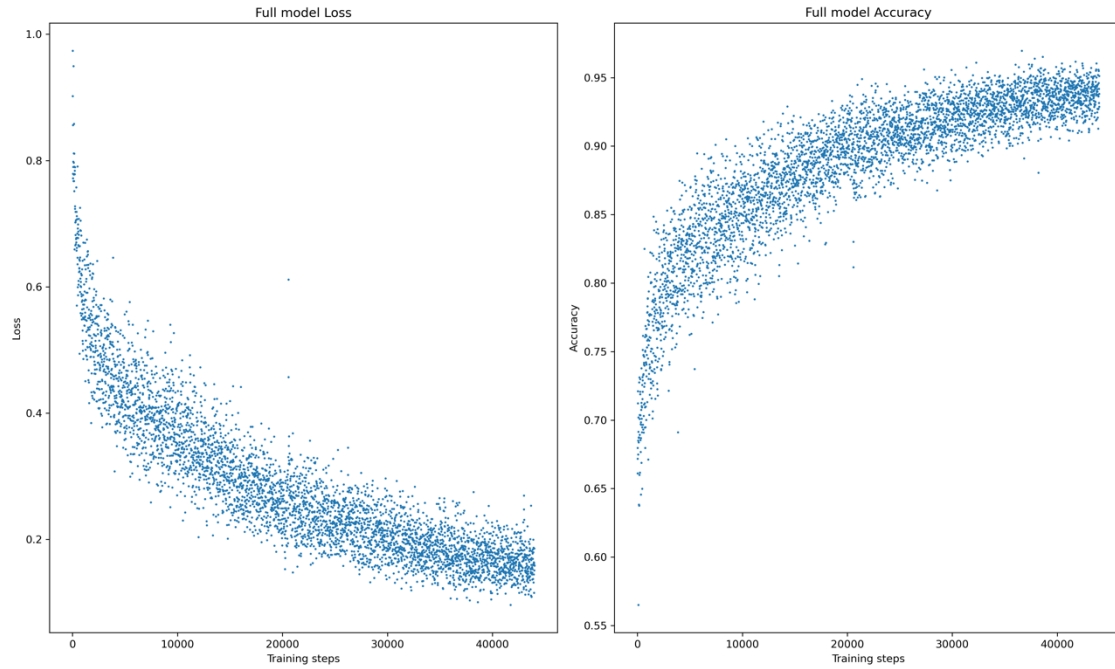
### 4.1. Model proposal based on fused vital signs results

Analyzing this data, in addition to the accelerometry signals which have already shown their importance for models of this type, we discovered that the physiological signal blood volume pulse (BVP) and electrodermal activity (EDA) have behavior that can help validate a fall. Based on that we proposed a model that take in considerations this signals in real time. We analyzed the performance of this proposal, and from the graph in **Figure 2** it is possible to observe that the model migrates to an accuracy close to 90%

in a much shorter time than in other models, showing that it has training data that tends to make the model converge faster. The metrics of the model in operation with real-time data through the wearable simulator are detailed in **Table 1**.

**Table 1. Model performance on LifeSeniorProfile test data**

Accuracy	Specificity	Precision	Recall/Sensitivity	F1-Score
0.97	0.99	0.90	0.84	0.87



**Figure 2. Loss and accuracy graphic for final model training process (Source: Author).**

#### 4.2. Model with user adaption analysis

As the previous sections have proven, the hypothesis that the behavior of vital signs is much more heterogeneous than the behavior of signals expected for movement sensors is fulfilled. Interpersonal behavior is highly variable, which tends to harm the models developed in the laboratory in real-use situations. As detailed in the methodology, we simulate a model capable of adapting to user behavior through a training process during the first use and through confirmation by the user whenever a fall is detected. This generates a collaborative model that aims to enrich training data with real information, which is difficult to reproduce in simulated environments. To simulate this behavior, we start from the fused model and evaluate its performance in detecting data from a new user with data not seen by the model. This new user performed the simulation of each activity twice, one used for training and the other used for testing the model. We evaluate the performance of the test data using the model from fused model and after collecting the results, we perform training with the new data. Later, we used the same test data in the latest model to evaluate whether the data from that user contributed to the improvement of the specific model for him and the general model.

In Table 2 we can see that the accuracy taking in account fall detection probability increase a lot when we tested this model using only data test from him (b), compared with previous model testing same data (a).

**Table 2. User adaptation model performance on LifeSeniorProfile specific user data.**

Model version	Accuracy	Specificity	Precision	Recall	F1-Score
a) Model with new data	0.85	0.93	0.44	0.33	0.38
b) User adapted with new data	0.91	0.92	0.58	0.85	0.69
c) User adapted with test data	0.69	0.94	0.98	0.63	0.77

In Table 2 we can also see that the increment of new data did not cause any harm to the overall performance of the model, as can be seen in part (c), where the model was tested with the same general test data used in the previous steps.

## 5. Discussion

Our model achieves significant results in real-time stream data, which is more difficult than traditional static analysis of test data. It shows that the correlation of vital signs with accelerometry data is relevant for detecting risk situations in the elderly. The initial results are promising and open doors for further experimentation.

Besides the promising results, the proposal model in this thesis has some limitations that need to be taken into consideration:

- Emulated falls: One of the critical limitations of our work, and most of them available in the literature, is that the datasets utilized for experimentation are emulated fall datasets. Our model proposes a user adaptation phase that aims to reverse the proportion between simulation and real-life over time.
- Limited number of volunteers - as the number of volunteers performing the simulated movements is not higher than other datasets, the researcher needs to consider specific algorithms; some insights can be the product of a poor number of collections and not from the algorithm performance;
- Age of volunteers - the average age of volunteers is lower than that of the elderly, generating a loss of specific characteristics found only in older adults. This choice prevents older adults from getting injured, even with the falls being controlled and assisted by a medical team. Since the subjects were young and healthy, will the model remain equally efficient for the elderly population, which is the target population? Will the user adaptation model be sufficient to convert this simulated scenario into another population range for an elderly user? These questions need further investigation, thus opening doors for future research directions;

We agree that the data used in this work do not exactly reflect the target population of the developed system, however, it is expected that the system's adaptability will be able to cushion these differences over time and through retraining.

## 6. References

- Anuradha, Singh, Rehman Saeed, Yongchareon Sira, and Chong Peter. 2020. "Sensor technologies for fall detection systems: A review." *IEEE Sensors Journal* (IEEE) 6889--6919.
- Warrington, Daniel, Elizabeth Shortis, and Paula Whittaker. 2021. "Are wearable devices effective for preventing and detecting falls: an umbrella review (a review of systematic reviews)." *BMC public health* 1--12.