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RESEARCH ON DEPLOYING MACHINE LEARNING ON LOW-PERFORMANCE MICROCONTROLLERS FOR HUMAN ACTIVITY RECOGNITION SYSTEMS USING ACCELEROMETER SENSORS

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The dissertation can be found at:

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INTRODUCTION

Human Activity Recognition (HAR) systems automatically monitor and classify daily activities, benefiting community healthcare. HAR can be applied to monitoring the physical activity level of post-operative patients [2], [3], assessing the effectiveness of rehabilitation, warning of fall risk in the elderly [4], [5] and tracking the training performance of athletes [6].

General objective of the dissertation: To research the deployment of machine learning on low-performance microcontrollers for accelerometer-based activity recognition systems, ensuring accurate real-time classification of basic activities.

Contributions of the dissertation

This dissertation differs from other studies by focusing on the efficient deployment of computationally simple algorithms for real-time activity classification on low-performance microcontrollers. The new findings of the dissertation are as follows:

- It demonstrates, for the first time, the feasibility of deploying machine learning (Random Forest, KNN) directly on the 8-bit PIC18F4520 microcontroller (1.5KB RAM) for real-time human activity recognition with an accuracy above 96%, using only 5 simple statistical features.

- It proposes and extends the recognition system to terrain with elevation changes (going up/down stairs), with a KNN algorithm that clearly distinguishes the two directions of movement, which previous studies on low-performance microcontrollers had not achieved.

Structure of the dissertation

Chapter 1: Reviews domestic and international HAR research, recognition methods, machine learning algorithms and sensor signal processing, and identifies the research gaps and directions of the dissertation.

Chapter 2: The author designs the RF4-HAR system, which recognizes four basic activities at low cost with real-time response. Data acquisition, preprocessing, feature extraction and classification are performed directly on an 8-bit microcontroller [CT1], [CT2], [CT5].

Chapter 3: Presents activity recognition on terrain with elevation changes through two systems: RF5-HAR, which uses the RF algorithm without distinguishing going upstairs from downstairs [CT3]; and KNN6-HAR, which uses the KNN algorithm to accurately distinguish going upstairs from downstairs [CT4].

Finally, the conclusion summarizes the main contributions of the dissertation and future research directions [CT6].

CHAPTER 1. OVERVIEW OF SENSOR-BASED ACTIVITY RECOGNITION SYSTEMS

Chapter 1 introduces the problem of human activity recognition using sensors. Related studies are grouped by approach. In general, there are three common approaches to HAR: vision-based, environment-interactive sensor-based and wearable sensor-based. Each approach suits different situations and environments. The challenges of sensor-based human activity recognition are also analyzed as a basis for the algorithms proposed in the following chapters. In addition, some background knowledge and common evaluation metrics for human activity recognition are presented in this chapter.

1.1. Introduction to human activity recognition

Today, HAR has become an active research field worldwide, driven by the rapid development of sensor technology and machine learning [1]. Many practical problems require solutions based on activity recognition, such as healthcare [2], [3], fall detection for the elderly [4], [5], industry [6] and security [24]. Activity recognition technology collects information about user behavior and provides various ways of interaction, enabling systems to actively support users in their work [25].

There are two common approaches to HAR: the vision-based approach and the sensor-based approach (including the environment-interactive sensor approach and the wearable sensor approach) [7], [8], Figure 1.1.

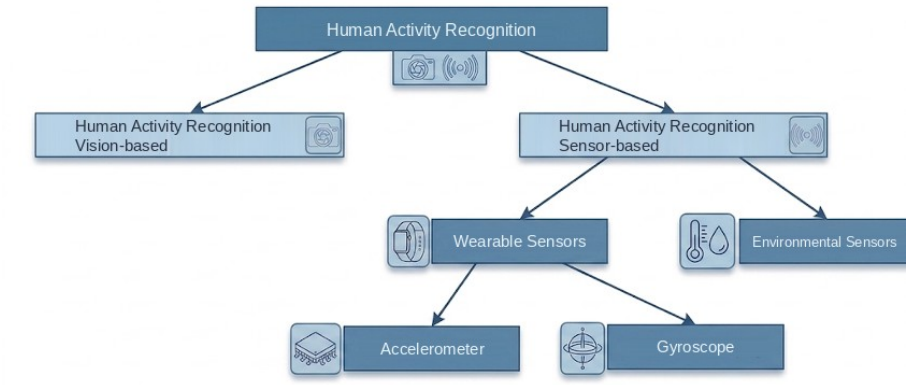


Figure 1.1. Classification of human activity recognition methods

A comparison of the recognition methods is shown in Table 1.1.

Table 1.1. Comparison of activity recognition methods

Method	Sensor	Advantages	Disadvantages	Accuracy
Vision [6]	Camera	Non-intrusive	High cost, privacy issues, limited field of view	85-90%
Environment sensors [6]	IR, pressure	Nothing to wear	High installation cost, not mobile	80-85%
Wearable sensors [8]	Accelerometer, gyro	Mobile, low cost	Must be worn continuously	95-99%

1.2. Overview of sensor-based activity recognition systems

1.2.1. Sensor-based activity recognition systems

Human activity recognition (HAR) aims to recognize activities that a person has performed or is performing from a series of observations of the person's actions and the surrounding environment. Activity classification using wearable sensors is an approach attracting much attention, owing to strong technological progress: sensors are increasingly small and light yet capable of robust data acquisition, allowing continuous, unrestricted operation.

1.2.2. Typical studies on wearable sensor-based activity recognition

Wearable sensors can be attached to the human body from head to toe and operate over a moderately large area while the wearer performs activities such as walking and running. Wearable sensors such as accelerometers and gyroscopes are often embedded in smartphones, smartwatches, smart wristbands, clothing, belts, glasses, helmets or shoes.

Activity analysis using accelerometers combined with machine learning algorithms has become a good choice and is the problem addressed by the author, with the requirements of a low-cost, easy-to-use system deployable on low-performance microcontrollers.

1.3. Accelerometer-based activity recognition systems

1.3.1. Typical studies on accelerometer-based activity recognition

Table 1.2 presents an overview of accelerometer-based HAR.

Table 1.2. Overview of HAR based on wearable sensors

Reference	No. of sensors	Sensor placement	Activity
Zheng et al. [39]	1	Waist, wrist, hip, pocket	Standing, Lying, Walking, Dancing, Running, Upstairs, Downstairs, Jogging, Jumping rope, Sitting
Gjoreski and Gams [40]	24	Right ankle, left thigh, chest	Sitting, Going down, Standing up, Lying, Sitting on the ground, Standing
Jiang et al. [41]	4	Right forearm, right shank, left forearm, left shank	Standing, Walking on an elliptical trainer, Sitting, Running on an elliptical trainer, Lying in bed, Cycling, Jogging, Rowing, Walking and weight lifting
Jennifer et al. [15]	1	Smartphone	Sitting, Jogging, Upstairs, Walking, Downstairs, Standing
Chun and Weihua [43]		Right thigh	Stand-to-sit, Sitting, Lie-to-sit, Standing, Lying, Sit-to-stand, Walking, Sit-to-lie
Siirtola and Roning, 2012 [44]	1	Smartphone in pocket	Cycling, Walking, Driving, Standing, Sitting
Sweetlin [45]	1	Chest	Falling, Walking, Standing, Lying, Sitting
Mannini et al. [46]	1	Wrist, ankle	26 daily activities
Lei et al. [47]	4	Chest, under left arm, waist and thigh	Standing, Stand-to-sit, Walking, Sitting, Lie-to-stand, Lying, Sit-to-stand, Downstairs, Stand-to-lie

1.3.2. Model of an accelerometer-based activity recognition system

The accelerometer collects motion data and sends it to the system. To classify human activities, the system receiving the sensor data (Figure 1.3) usually goes through the following steps: data acquisition (raw data collection and preprocessing), feature selection (segmentation and feature extraction) and activity classification (training, followed by classification).

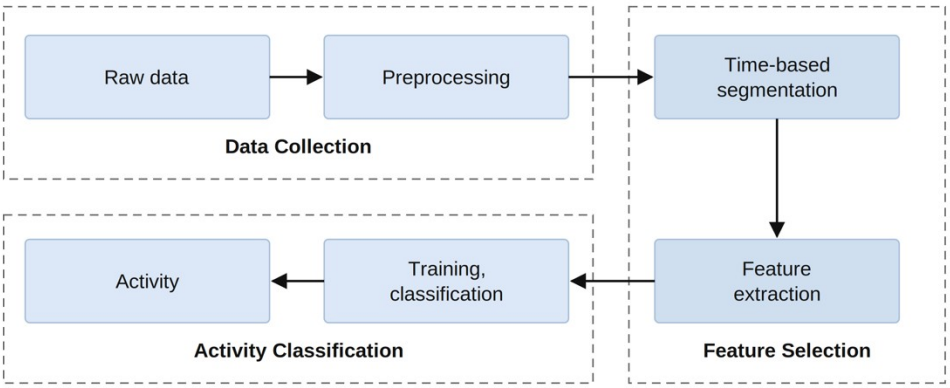


Figure 1.3. Model of a human activity classification system

1.3.3. Model evaluation methods

The performance of a classification model is usually evaluated on a test dataset. The most common way to measure performance is the confusion matrix, which compares actual and predicted outputs to assess classification accuracy. Common metrics include overall accuracy, sensitivity, PPV (positive predictive value) and NPV (negative predictive value).

1.4. Conclusion of Chapter 1

This chapter has presented an overview of activity recognition systems based on wearable sensor data. Wearable sensor-based activity recognition has attracted much attention from the research community and has been applied in many fields, from security and industry to sports and the arts, and especially in healthcare. Among sensors, the accelerometer is the most widely used in activity recognition studies and yields high classification performance. Chapter 1 also presented a general system with 3 main steps for recognizing activities from wearable sensor data.

CHAPTER 2: RECOGNITION OF BASIC ACTIVITIES USING RANDOM FOREST ON AN 8-BIT MICROCONTROLLER (RF4-HAR)

In this chapter, the dissertation presents in detail the proposed method for recognizing four basic human activities (standing, sitting, walking, jogging) using 3-axis accelerometer data and the Random Forest machine learning algorithm. The chapter covers: the design of a real-time system on the PIC18F4520 microcontroller; the hardware design of the IoT system with sensor, processing, communication and power modules; the data used, the proposed processing and classification procedure, performance metrics, experimental results with four machine learning algorithms and an analysis of the results. The algorithmic basis and initial feature set were published in [CT1]; the embedded implementation with the four activities of the RF4-HAR system was published in [CT2]; some related results were published in [CT5].

2.1. Model of the RF4-HAR system

2.1.1. Architecture of the activity classification model

The dissertation uses supervised learning. The overall approach to this HAR problem consists of three stages: raw data collection, model analysis and activity classification (deployment and evaluation), as shown in Figure 2.1.

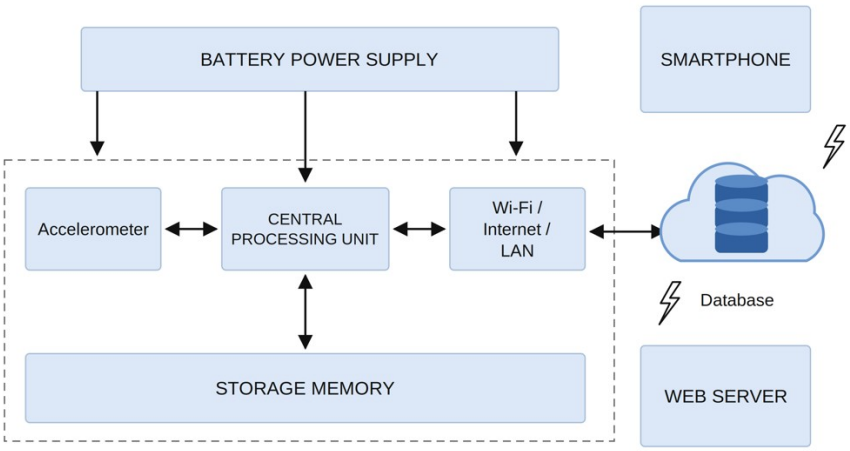
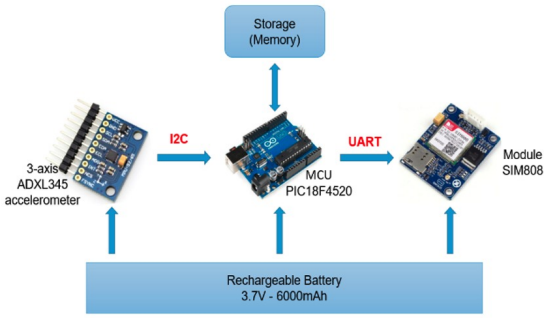


Figure 2.1. Block diagram of the activity classification process

The proposed system integrates a sensor, a low-cost IMU and a wireless data transceiver into a wearable device to support activity classification. The structure of the proposed system is illustrated in Figure 2.2.



(a)



(b)

Figure 2.2. Model of the proposed device (a) and a volunteer wearing the device (b)

The ADXL345 3-DOF accelerometer is connected to the PIC18F4520 microcontroller via the I2C interface to collect data along three axes; in Chapter 2, the SIM808 (GSM/GPRS) module communicates with the MCU via UART. The PIC18F4520 was deliberately chosen to demonstrate feasibility on the lowest-cost 8-bit microcontroller (2 USD): 40 MHz clock, 1.5KB RAM, 32KB Flash. The experiments were run on a Dell E6540 laptop with a 2.7 GHz processor and 8GB RAM.

2.1.2. Datasets

This dissertation uses two human activity datasets: a self-collected dataset focusing on basic human activities and a public dataset containing similar activities.

Collected dataset

The author recorded experimental data from a total of 16 volunteers in two groups: a student group of 14 people (7 male and 7 female), aged 18-22, height 1.56-1.8 m, weight 43-72 kg; and an elderly group of 2 people (1 male and 1 female), aged 65 and 72, height 1.4 m and 1.46 m, weight 42 kg and 46 kg. The device was worn on the belt with a sampling frequency of 50 Hz and recorded four states: Standing for 40 minutes, Sitting for 30 minutes, Jogging for 10 minutes and Walking for 22 minutes.

A detailed description and some illustrations of the activities are given in Table 2.1 below.

Table 2.1. Explanation of activity concepts

Activity	Description
Sitting	Head and back not touching the floor, legs at rest, back slightly reclined
Standing	Upright body, feet not moving
Walking	Upright body moving slowly to different positions, with at least one foot on the ground
Jogging	Upright body moving quickly to different positions, with both feet off the ground at some moment

In addition, to test the performance of the algorithm, the public WISDM dataset was used [15].

2.1.3. Data processing procedure

Data segmentation for activities

The dissertation adopts the sliding-window approach to segment the data because of its simplicity and suitability for real-time applications; the window size is a hyperparameter that must be investigated experimentally [15], [48].

For the public dataset, the number of activity observations using a 10-second window (with 40% overlap) is presented in Table 2.2. The extracted dataset contains a total of 10,482 observations from 36 participants.

Table 2.2. Composition of activity observations - public dataset

Activity	**No. of observations**
Standing	445
Sitting	548
Jogging	3258
Walking	6231
Total	10482

In the experiment, 16 volunteers wore the device on the belt (Figure 2.2) while performing a series of specific activities. Table 2.3 presents the number of activity observations using a 10-second window (with 40% overlap). The extracted dataset contains a total of 1,283 observations.

Table 2.3. Composition of activity observations - self-collected dataset

Activity	**No. of observations**
Standing	517
Sitting	383
Jogging	60
Walking	265
Total	1283

Feature extraction

To achieve high classification performance, selecting features that support the activities is extremely important. Feature selection is performed before feature extraction. For feature selection, part of the data (the first 200 samples) obtained from the X-axis acceleration of each activity is plotted in Figure 2.4 to determine the range and characteristics of each activity.

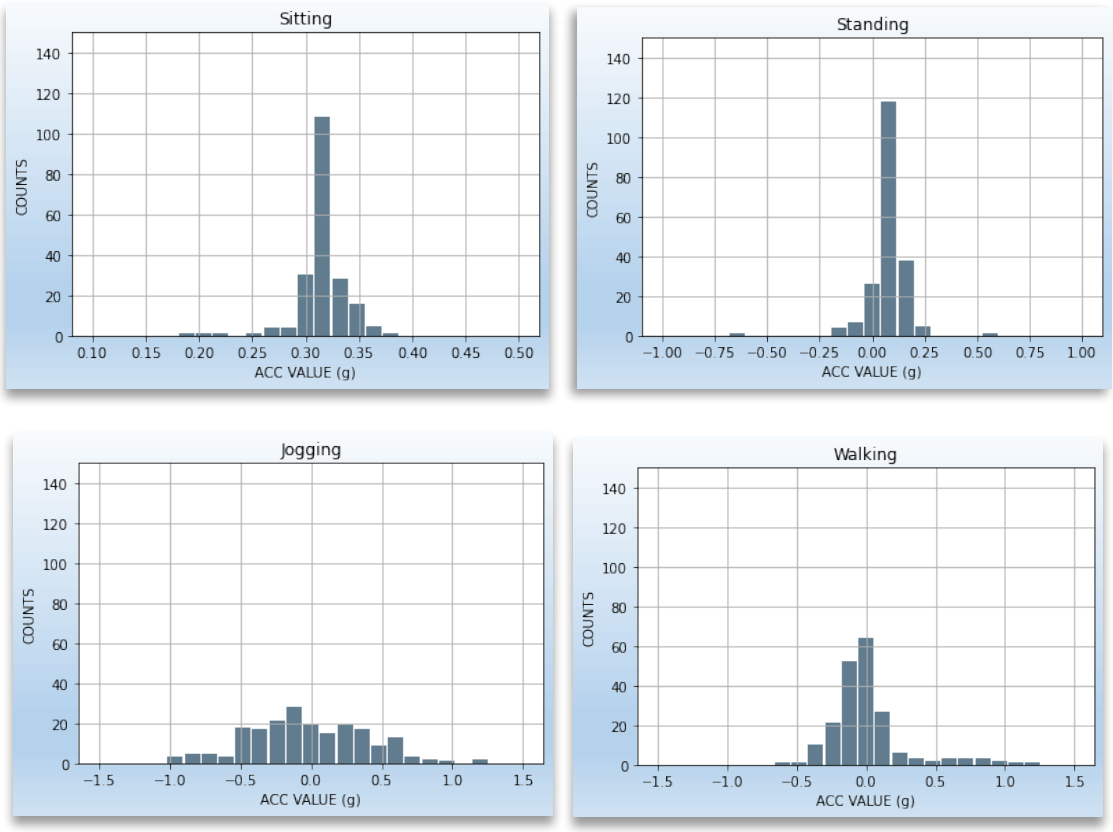


Figure 2.4. Distribution of X-axis acceleration data for each activity

From Figure 2.4, static states (Standing, Sitting) have values within a specific small range. For example, Standing is concentrated at ax ≈ 0g (1g = 9.8 m/s2), while Sitting along the X-axis is centred between 0.12g and 0.36g. Therefore, two features, the mean and the median, can be chosen to measure data concentration in order to distinguish static from dynamic states and to classify static states from each other. In addition, dynamic states such as Jogging and Walking have a wider range of values than static states, so the range was chosen to capture the difference between their highest and lowest values.

Table 2.7. Features computed on the X-axis

Feature	**Formula**	
Mean	$\mu(X_j) = \frac{1}{N}\sum_{i=1}^{N} x_i$	(1)
SD - standard deviation	$\sigma_{(X_j)} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2}$	(2)
Median , Xj sorted	$median(X_j) = \frac{x_{\lfloor N/2+1 \rfloor} + x_{\lfloor N/2 \rfloor}}{2}$	(3)
Range	$range(X_j) = \left[\min_{i=1}^{N}\left(x_i\right), \max_{i=1}^{N}\left(x_i\right)\right]$	(4)
RMS	$RMS_{X_j} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	(5)

Using the five features above, the dataset was divided into two parts: training and test sets of 60% and 40%, respectively.

2.2. Experiments and results

The performance of each classifier was compared in terms of overall accuracy (acc) (Figure 2.7) and sensitivity (Figure 2.8) on the public dataset with window sizes of 5 s, 8 s, 10 s, 12 s and 15 s. The RF classifier gave the best results on both measures: an accuracy of 95.3% and a sensitivity of 94% with a 10-second window.

2.2.1. Experimental results of the algorithms

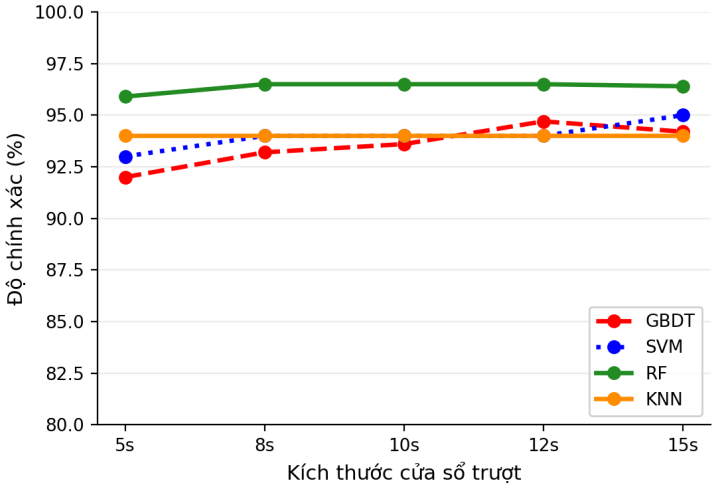


Figure 2.7. Accuracy on the public dataset

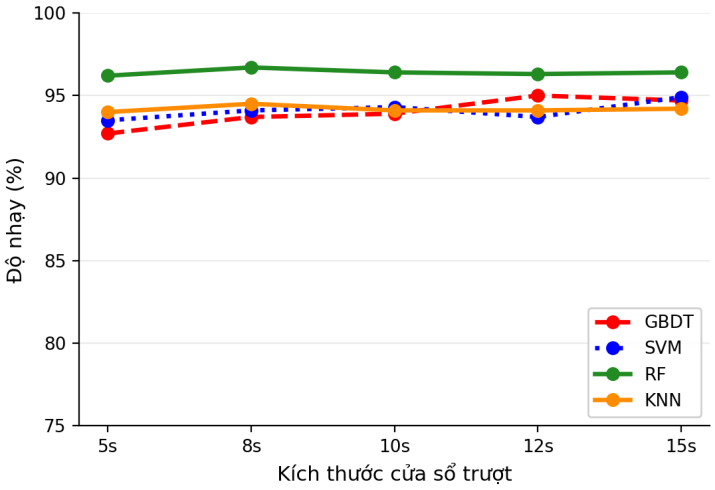


Figure 2.8. Sensitivity on the public dataset

Similarly to the public dataset, on the self-collected dataset with different classifiers and window sizes, KNN gave the highest accuracy (100%) and the RF classifier the highest sensitivity (99.8%) with an 8-second window.

2.2.2. Implementation of the RF model on the microcontroller

The detailed results of the RF classifier are shown by the confusion matrices of the public data (Table 2.8) and the recorded data (Table 2.9). In Table 2.8, most test samples are relatively well discriminated (166/177 Standing, 208/218 Sitting, 1137/1302 Jogging, 2481/2491 Walking samples). However, 173 samples are misclassified between Jogging and Walking, while only 12 samples are misclassified between Standing and Sitting.

Table 2.8. Confusion matrix - public dataset

Activity Observed	Predicted activity			
	Standing	Sitting	Jogging	Walking
Standing	**166**	7	0	2
Sitting	3	**208**	0	24
Jogging	0	0	**1137**	165
Walking	0	2	25	**2481**

Table 2.9. Confusion matrix - self-collected dataset

Activity Observed	Predicted activity			
	Standing	Sitting	Jogging	Walking
Standing	**206**	0	0	0
Sitting	0	**151**	1	0
Jogging	0	0	**44**	2
Walking	0	0	1	**104**

2.2.3. Performance evaluation of the RF classification model

The overall performance on the datasets using two metrics (micro-average and macro-average) is shown in Table 2.12 for the best-performing RF classifier. The micro-average results are relatively high (>95% on the public dataset and >99% on the author's dataset). The macro-average evaluation, which computes each class independently and then averages, gives slightly lower results: >94% on the public dataset and >98% on the author's dataset.

Table 2.12. Metrics for evaluating the performance of the classification model

Evaluation method	Micro-average		Macro-average	
	Public dataset	Author's recorded dataset	Public dataset	Author's recorded dataset
Accuracy	97.7%	99.6%	97.7%	99.6%
Sensitivity	95.3%	99.2%	94.0%	98.5%
PPV	95.3%	99.2%	96.5%	98.4%
NPV	98.4%	99.7%	98.3%	99.8%
AUC	99.4%	99.8%	99.3%	99.7%

2.3. Conclusion of Chapter 2

Chapter 2 has presented in detail the proposed method for recognizing four basic human activities (standing, sitting, walking, jogging) using data from the ADXL345 3-axis accelerometer and machine learning algorithms. The main results of the chapter are as follows:

The author successfully embedded a low-complexity algorithm into a low-performance microcontroller. The experiments show that the RF classifier outperforms GBDT, SVM and KNN with a 10-second window, with a model size of ~1.2KB Flash, an inference time of ~45ms per classification and an accuracy of 97.7%. Daily activities of different individuals can be accurately classified with a simple set of five features.

For long-term activity recognition, the proposed device does not cause significant discomfort or restriction during activities. The accelerometer is low-cost and small, and the proposed device costs only 15 USD. To reduce power consumption, a low sampling rate (50 Hz) is used to extend battery life; the device is also easy to install and use. The scientific publications related to this chapter are [CT1] and [CT2].

The basic human activities (standing, sitting, walking, jogging) in Chapter 2 were recognized on flat terrain. Based on these results, the four algorithms (GBDT, SVM, RF, KNN) were further tested to extend the research to terrain with elevation changes, i.e., high-rise buildings, additionally recognizing going upstairs and downstairs with a real-time system on the PIC18F4520 microcontroller, as presented in detail in Chapter 3.

CHAPTER 3: ACCELEROMETER-BASED ACTIVITY RECOGNITION ON TERRAIN WITH ELEVATION CHANGES

Chapter 3 extends the research from 4 basic activities on flat terrain to 5-6 activities in high-rise buildings. Recognizing the potential confusion between Upstairs and

Downstairs in the data, the RF5-HAR system merges these two activities into a single Stairs category, improving the accuracy and reliability of the classification system and achieving a recognition rate above 98% [CT3]. Next, the KNN6-HAR system uses the K-Nearest Neighbors (KNN) algorithm to distinguish going upstairs from going downstairs [CT4]. Activity selection and feature extraction are optimized and adapted to the constraints of low-performance microcontrollers.

3.1. Improved method for monitoring activities in buildings - RF5-HAR

3.1.1. Method description

The Random Forest (RF) algorithm is embedded directly in the microcontroller, enabling real-time activity classification. RF was chosen for its balance between accuracy and computational efficiency, making it suitable for resource-constrained devices. By exploiting the simplicity of accelerometer data and the efficiency of RF, the system achieves effective and cost-efficient activity recognition, even on low-cost microcontrollers.

The system model and devices are similar to those of the RF4-HAR system presented in Chapter 2.

3.1.2. Dataset and improved algorithm

Five activities, Standing, Sitting, Jogging, Walking and Stairs, were collected from 16 volunteers with the device worn on the belt (sampling frequency 50 Hz). A detailed description of the activities is given in Table 3.1 below.

Table 3.1. Explanation of activities

Activity	**Description**
Standing	Standing naturally and steadily
Sitting	Sitting on a chair
Jogging	Running steadily and slowly
Walking	Normal walking
Stairs	Going up or down the stairs step by step

The flowchart of the proposed random forest algorithm for real-time classification is illustrated in Figure 3.1 below.

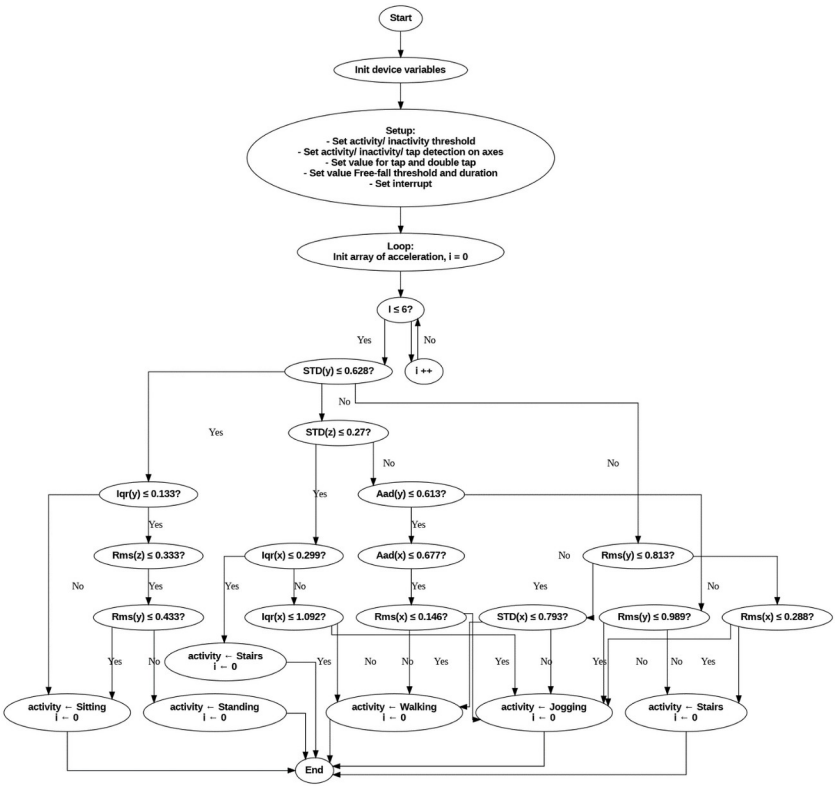


Figure 3.1. Embedded program for real-time activity classification

3.1.3. Data processing procedure

Data segmentation for activities

After the data were received from the accelerometer, they were aggregated and used to analyze activity features. The data were divided into small segments, each containing information related to an activity. This segmentation is necessary because of the sequential nature of activities, which complicates the definition of activity boundaries.

With an 8-second window (40% overlap), the WISDM dataset contains 16,381 observations (Table 3.2).

Table 3.2. Activity data from the WISDM dataset

Activity	**Total observations**
Standing	695
Sitting	857
Jogging	5093
Walking	6355
Stairs	3381
Total	16381

During the experiment, 16 volunteers performed the activities in Table 3.1 while wearing the device on the belt. Table 3.3 shows the number of activities from the

collected dataset using an 8-second window (with 40% overlap). The extracted dataset contains a total of 6,299 observations.

Table 3.3. Activity data from the collected dataset

Activity	Total observations
Standing	1459
Sitting	1179
Jogging	989
Walking	1459
Stairs	1213
Total	6299

Feature selection for improved performance

Table 3.4. Feature formulas for X-axis acceleration data

Feature	Formula	
AAD	$\frac{1}{n}\sum_{j=1}^{n} x_j - Mean(x)$	(1)
STD	$\sigma(X_i) = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(x_j-\mu)^2}$	(2)
IQR	Q3 - Q1	(3)
Range	$range(X_i) = \left[\min_{j=1}^{N}\{x_j\}, \max_{j=1}^{N}\{x_j\}\right]$	(4)
RMS	$RMS_{X_i} = \sqrt{\frac{1}{N}\sum_{j=1}^{N} x_j^2}$	(5)

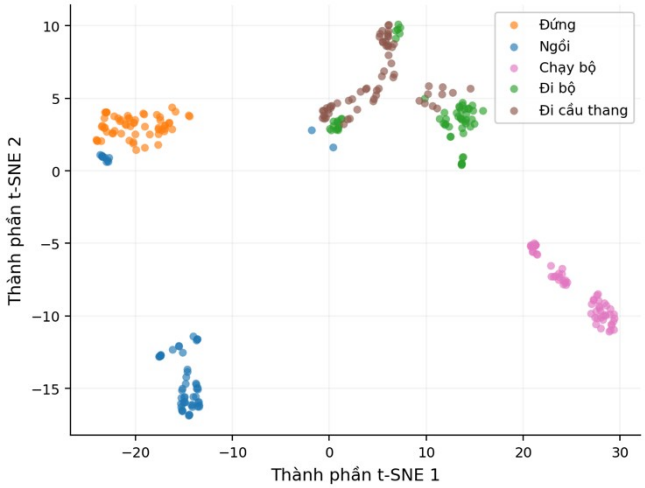


Figure 3.4. WISDM dataset represented in 2D space: (a) without features and (b) with features

The five features AAD, STD, IQR, Range and RMS are also used with the collected dataset as with the WISDM dataset. The t-SNE representation shows that the activities in the collected dataset are clearly separated, although there is still slight overlap among Jogging, Walking and Stairs.

3.2. Experiments and results of the RF5-HAR system

3.2.1. Experimental results of the algorithms

On the WISDM dataset, the RF classifier performs best, with an accuracy of 96.5% and a sensitivity of 96.4% for an 8-second window; on the collected dataset, RF achieves an accuracy of 98.3% and a sensitivity of 97.5% with the same window size.

3.2.2. Implementation of the RF algorithm on the microcontroller

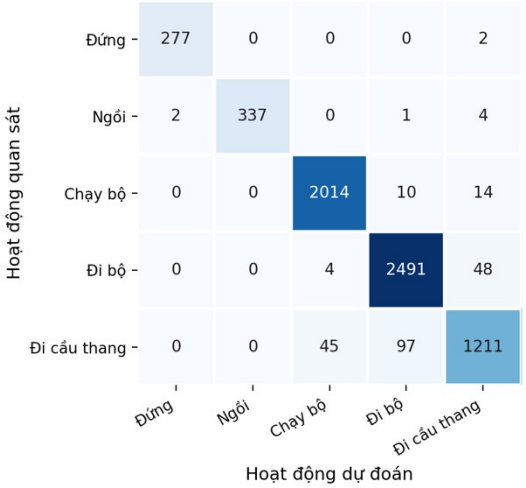


Figure 3.6. Confusion matrix of the RF algorithm on the WISDM dataset with an 8-second window

3.2.3. Evaluation of the RF classification model

The overall performance is evaluated with both macro-averaging and micro-averaging. The results in Table 3.15 show that the RF classifier is the best-performing model: micro-averaging yields performance above 96% on the WISDM dataset and above 98% on the collected dataset.

Table 3.15. Evaluation of the RF classification model with an 8-second window

Metric	**Micro-average (%)**		**Macro-average (%)**	
	Public dataset	***Collected dataset***	***Public dataset***	***Collected dataset***
Accuracy	96.51	98.03	98.61	99.21
Sensitivity	96.71	97.54	96.71	97.13
PPV	96.71	97.54	97.48	97.09
NPV	98.90	99.52	99.07	99.52

3.3. Evaluation of the RF5-HAR system

3.3.1. Comparison with previous studies

Compared with studies using 43 or 64 features [18], [23], the RF5-HAR system uses only five statistical features yet still achieves high accuracy. The CNN model of Chen et al. achieved an average accuracy of 93.8% [50] but requires substantial computing resources; Vavoulas et al. [18] achieved higher accuracy on WISDM but used 64 features executed on a PC.

3.3.2. Evaluation of the applicability and deployment of the RF5-HAR system

In assisted-living systems, achieving user acceptance is an important challenge. Although computer vision approaches offer promising applications, their deployment may be hindered by privacy concerns. Elderly users may be reluctant to have their images monitored or recorded. In this regard, a belt-worn device with embedded sensors offers a practical solution; the classification results are displayed on a smartphone (Figure 3.8).

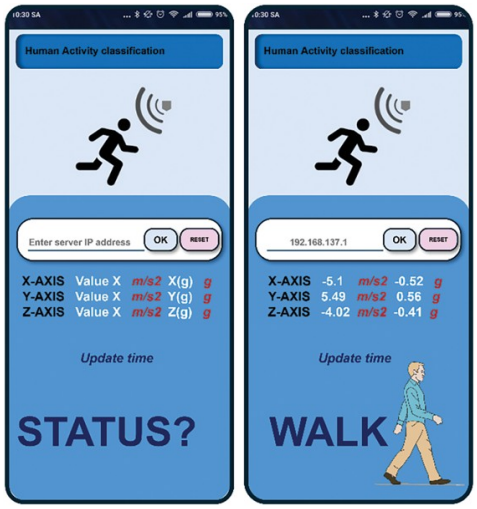


Figure 3.8. Classification performed by the real-time microcontroller and displayed on a smartphone

3.4. The KNN6-HAR system distinguishing upstairs and downstairs activities

3.4.1. Architecture of the activity classification model

The system model and wearable device are arranged similarly to the RF4-HAR system. The steps in activity recognition are described in Figure 3.9.

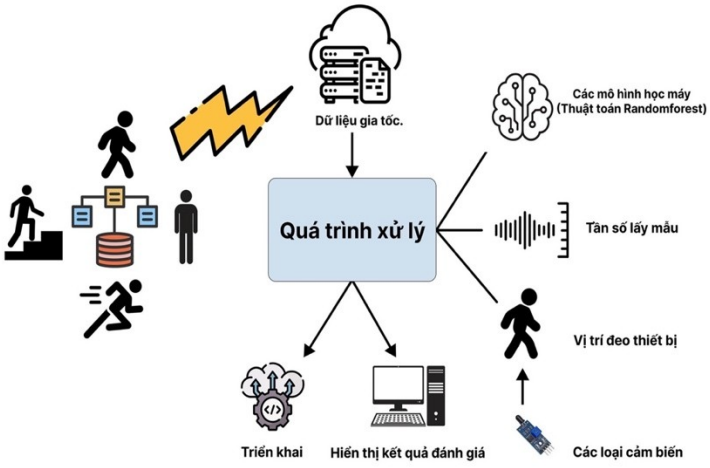


Figure 3.9. Steps in activity recognition

3.4.2. Datasets

Collected dataset

The system uses the ADXL345 3-DOF accelerometer to collect motion data, configured with a ±4 g full scale, a sensitivity of 128 LSB/g and a noise level of 150 µg. The ADXL345 is connected to the PIC18F4520 microcontroller via I2C; data transmission is handled by the ESP8266 module communicating with the MCU via UART.

Experimental data were recorded from 16 volunteers (14 students aged 18-22 and 2 elderly people aged 65 and 72), with the device fixed on the belt and a sampling

frequency of 50 Hz. Six activities were recorded: Standing (40 minutes), Sitting (30 minutes), Jogging (10 minutes), Walking (22 minutes), Downstairs (20 minutes) and Upstairs (20 minutes).

Public dataset

The public WISDM dataset [15] was collected from 36 participants and includes six activities: Standing, Sitting, Jogging, Walking, Downstairs and Upstairs. A detailed description of the activities is given in Table 3.16.

Table 3.16. Description of activities

Activity	Description
Standing	Standing naturally and steadily.
Sitting	Sitting on a chair.
Jogging	Running at a steady, slow pace.
Walking	Normal walking.
Downstairs	Walking down the stairs one step at a time
Upstairs	Walking up the stairs one step at a time

In this study, the focus is on embedding the algorithm directly in the device for real-time activity recognition. KNN adapts well to nonlinear data and is easy to update with new data, improving the accuracy and robustness of the model. Therefore, the activity classification algorithm proposed for embedding in the wearable device is KNN.

3.4.3. Data processing procedure

Data segmentation for activities

Table 3.17 presents the total number of activity observations obtained from the public and collected datasets. For the public data, with a 15-second sliding window and 40% overlap, the extracted dataset contains 10,476 observations. For the collected data, with an 8-second window and 40% overlap, there are 9,745 observations.

Table 3.17. Activity data from the public and collected datasets

Activity	Total public	Total collected
Standing	445	2271
Sitting	548	1769
Jogging	3253	1563
Walking	4067	2209
Downstairs	978	905
Upstairs	1185	1028
Total	10476	9745

Feature extraction

To achieve high classification performance, selecting features that carry activity information is extremely important. The distribution of the first 400 X-axis acceleration samples of each activity helps determine the range and select suitable features. This visual analysis guided the selection of four main statistical features: Variance (Var), Mean Absolute Value (SAV), Skewness (Skew) and Peak-to-Peak (P2P, equivalent to the Range feature in Chapter 2).

Table 3.18 presents the formulas of the four features Var, SAV, Skew and P2P computed on the X-axis; the same formulas are used for the Y and Z axes.

Table 3.18. Feature formulas for X-axis acceleration data

Feature	**Formula**	
Var	$s^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2$	(1)
SAV	$S = \sum_{i=1}^{N}\lvert x_i\rvert$	(2)
Skew	$\frac{N}{(N-1)(N-2)}\sum_{i=1}^{N}\left(\frac{x_i - \bar{x}}{s}\right)^3$	(3)
P2P	$x_{\max} - x_{\min}$	(4)

3.5. Experiments and results of the method distinguishing upstairs and downstairs activities

Figures 3.13 and 3.14 show the overall accuracy and sensitivity of the DT, KNN, SVM and LR algorithms on the public dataset. The performance of each classifier varies with the time-window size (5 s, 10 s, 15 s, 20 s). Among these classifiers, KNN achieves

the best classification performance, with an accuracy of 96% for a 15-second window and a sensitivity of 87% for a 5-second window.

3.5.1. Experimental results of the algorithms

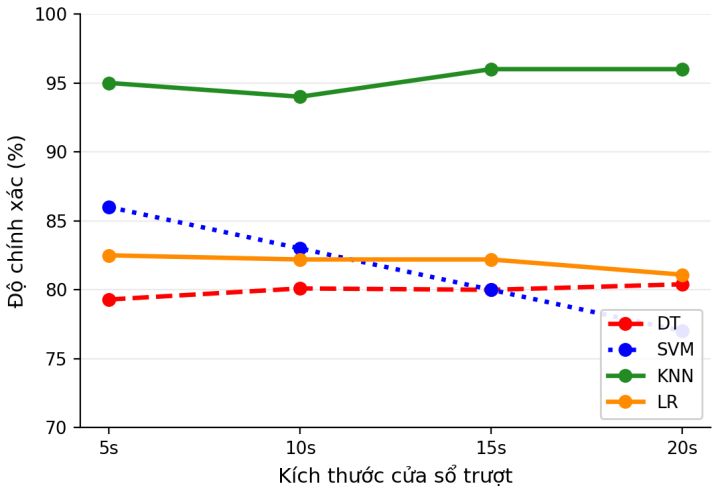


Figure 3.13. Accuracy of DT, SVM, KNN and LR on the public dataset

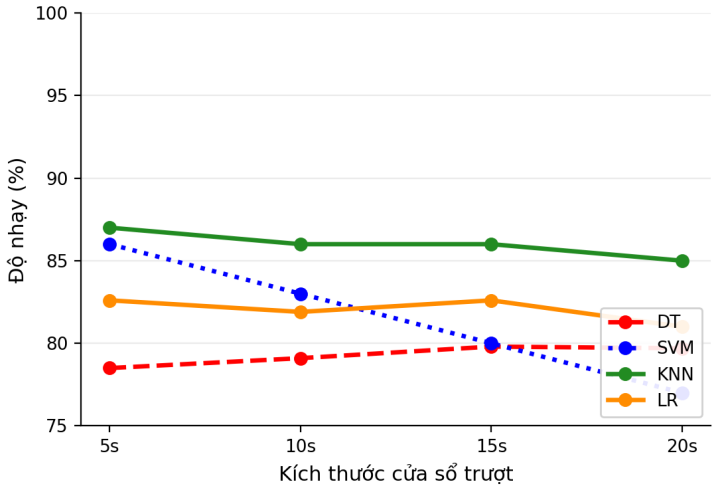


Figure 3.14. Sensitivity of DT, SVM, KNN and LR on the public dataset

3.5.2. Implementation of the KNN model on the microcontroller

Table 3.22 shows the detailed results of using the KNN algorithm to classify activities on the public dataset. The model discriminates Standing, Sitting, Jogging and Walking well, but there is still confusion between Downstairs and Upstairs because the acceleration data of these two activities are similar.

Table 3.22. Confusion matrix of the KNN algorithm on the public dataset

Activity Observed	Predicted activity						Total
	Standing	***Sitting***	***Jogging***	***Walking***	***Downstairs***	***Upstairs***	
Standing	**43**	1	0	0	5	2	149
Sitting	0	**181**	1	0	0	2	184
Jogging	0	0	**1014**	54	13	4	1085
Walking	1	0	19	**1264**	22	17	1356
Downstairs	5	0	31	71	**175**	48	327
Upstairs	3	0	27	53	34	**236**	396
Total	150	182	1112	1478	258	317	**3497**

3.5.3. Performance evaluation of the KNN classification model

Evaluating the overall performance with both macro-averaging and micro-averaging, Table 3.26 shows that KNN is the best-performing classifier: the micro-average accuracy reaches 86.1% (public) and 96.03% (collected), and the sensitivity reaches 82.1% (public) and 95.06% (collected).

Table 3.26. Evaluation of the KNN classification model

Metrics	Micro-average (%)		Macro-average (%)	
	Public dataset	***Collected dataset***	***Public dataset***	***Collected dataset***
Accuracy	86.1	96.03	85.4	95.1
Sensitivity	82.1	95.06	82.1	95.06
PPV	85.4	95.1	85.4	95.1
NPV	85.4	95.1	82.1	95

3.6. Evaluation of the KNN6-HAR system distinguishing upstairs and downstairs activities in high-rise buildings

3.6.1. Comparison with previous studies

While other studies use 43-64 features on PCs, smartphones or Raspberry Pi, KNN6-HAR is implemented directly on the 8-bit PIC18F4520 MCU with 12 features. Büber

and Guvensan [53] achieved 91.06% on a smartphone, lower than the proposed system (96.03% on the collected dataset).

3.6.2. Comparison with the RF5-HAR system

RF5-HAR classifies 5 activities while KNN6-HAR classifies 6, so their difficulty differs and a direct comparison is not possible. Table 3.27 gives an overall comparison of the effectiveness of the two systems.

Table 3.27. Overall comparison of the effectiveness of the RF5-HAR and KNN6-HAR systems

Criterion	**RF5-HAR**	**KNN6-HAR**	**Remarks**
Recognized activities	5 activities	**6 activities**	KNN6 has 1 more activity
Distinguishes up/down stairs	No	**Yes - accurate**	KNN6 superior
Overall Acc (PD)	96.5%	86.1%	RF5 higher
Overall Acc (CD)	98.3%	**96.03%**	KNN6 fairly good
Acc upstairs / downstairs	N/A, merged	**95.1% / 96.2%**	KNN6 specialized
Inference time	**50ms**	82ms	RF5 39% faster
Real time (<100ms)	Pass	Pass	Both meet the requirement
Model size	1.3KB	**0.1KB**	KNN6 13 times smaller
Suitable application	Flat terrain or no up/down distinction	**High-rise buildings**	KNN6 more suitable

3.7. Conclusion of Chapter 3

Chapter 3 has successfully achieved three major goals: extending the number of recognized activities, implementing algorithms on a low-performance microcontroller, and providing a comprehensive comparative evaluation with international studies. The main contributions are:

(1) Further extending activity monitoring in buildings with the RF5-HAR system for basic activities including stair walking [CT3], achieving an accuracy above 98.3% on the collected dataset, with great application benefits.

(2) Analyzing in detail the limitations of the RF5-HAR system and proposing an improved method with the KNN6-HAR system [CT4], which classifies 6 activities with an accuracy of 96.03% on the collected dataset.

CONCLUSION AND RECOMMENDATIONS

1. Conclusion

The dissertation has achieved its goal of developing an accelerometer-based human activity recognition (HAR) system with machine learning that accurately classifies basic activities in real time at low cost. The main results are:

Chapter 1 systematized the theoretical basis of HAR and machine learning methods. The detailed analysis shows that the wearable sensor approach is the most suitable for personal health monitoring thanks to its mobility, respect for privacy and low cost.

Chapter 2 successfully built a system recognizing 4 basic activities (Standing, Sitting, Walking, Jogging) with accuracies of 97.7% (WISDM) and 99.6% (collected data), outperforming previous studies; proposed an optimal feature set of only 5 simple statistical features (Mean, STD, Median, Range, RMS); built a 16-volunteer dataset with a standardized procedure; and evaluated it with multiple metrics (Accuracy, Sensitivity, PPV, NPV).

Chapter 3 extended the system: RF5-HAR recognizes 5 activities with accuracies of 96.5% (WISDM) and 98.3% (collected data) in real time for monitoring in buildings; KNN6-HAR recognizes 6 activities (distinguishing upstairs and downstairs) with accuracies of 86.1% and 96.03% on the public and collected datasets; a low-cost device (<20 USD) was built with the ADXL345 and PIC18F4520.

2. Recommendations

2.1. Applications in healthcare

Monitoring the physical activity of chronic patients: patients with cardiovascular disease, diabetes or hypertension must maintain prescribed activity levels. With accuracy above 96% and the ability to distinguish activity intensity (walking vs. jogging, upstairs vs. downstairs), the system helps doctors assess progress and adjust treatment.

Fall detection for the elderly: falls are a leading cause of death and injury in people over 65. The system can be extended to detect falls from abnormal patterns (a sudden high acceleration followed by prolonged lying).

Assessment of mobility and rehabilitation: stair climbing ability is an important indicator of cardiovascular and musculoskeletal health. The system can track the progress of patients after surgery or injury, providing objective data for physiotherapists.

2.2. Applications in security and monitoring

Monitoring lone workers and rescue personnel: rescuers, firefighters, guards, patrol officers and forest rangers often work alone over large areas. The system can monitor their safety and automatically alert the control center when prolonged immobility or an abnormal pattern is detected [CT6].

LIST OF PUBLISHED SCIENTIFIC WORKS

JOURNAL ARTICLES

[CT1] Q. H. Nguyen, D. N. Tran, T. H. Dao, D. T. Tran, **T. T. Vu**, and X. T. Do, "A method of building a real-time human behavior recognition system based on machine learning algorithms," *Res. Dev. Inf. Commun. Technol.*, vol. 2022, no. 2, pp. 83-88, 2022, doi: 10.32913/mic-ict-research-vn.v2022.n2.1137. ISSN: 1859-3526.

[CT2] **T. T. Vu**, T. T. Nguyen, D. N. Tran, N. S. Nguyen, and D. T. Tran, "An IoT solution that classifies human physical activities based on sensors and supervised learning algorithms," *Res. Dev. Inf. Commun. Technol.*, vol. 2024, no. 2, pp. 74-80, Nov. 2024, doi: 10.32913/mic-ict-research-vn.v2024.n2.1292. ISSN: 1859-3526, eISSN: 1859-3534.

[CT3] M. T. Vi, D. N. Tran, **T. T. Vu**, N. L. Nguyen, and D. T. Tran, "Efficient real-time devices based on accelerometer using machine learning for HAR on low-performance microcontrollers," *Comput. Mater. Contin.*, vol. 81, no. 1, pp. 1729-1756, 2024, doi: 10.32604/cmc.2024.055511. ISSN: 1546-2218, eISSN: 1546-2226 (SCIE, Q2).

[CT4] **T. T. Vu**, D. N. Tran, D. T. Tran, T. T. Bui, D. T. Vu, T. P. A. Nguyen, C. P. K. Phung, K. T. Pham, and M. T. Vi, "Effective human activity recognition through accelerometer data," *Eng. Technol. Appl. Sci. Res.*, vol. 14, no. 5, pp. 16499-16510, Oct. 2024, doi: 10.48084/etasr.8211. ISSN: 2241-4487, eISSN: 1792-8036 (Scopus, Q2).

CONFERENCE PAPERS

[CT5] **T. T. Vu**, D. T. Tran, P. P. Nguyen, N. S. Nguyen, and D. N. Tran, "An IoT solution for detecting human physical activities to support health status assessment based on sensors and supervised machine learning algorithms," in *Proc. VNICT 2025*, Ninh Binh, Vietnam, Nov. 2025, pp. 361-366. ISBN: 978-604-45-1878-7.

PATENT

[CT6] D. T. Tran, H. D. Vu, **T. T. Vu**, M. T. Vi and D. N. Tran, "System for detecting, alerting, and protecting sleepwalkers using a wrist-worn device, safety belt, and smart lock," Vietnam Patent No. 57548, granted under Decision No. 47085/QĐ-SHTT, Mar. 26, 2026.