An IoT Solution that Classifies Human Physical Activities based on Sensors and Supervised Learning Algorithms

Vu Thi Thuong [1,5], Thu Nguyen Thi [2], Tran Duc Nghia[3,*],Nguyen Nhu Son [3], Tran Duc Tan[4]
[1] Phuong Dong University, Hà Nội, Vietnam
[2] Faculty of Electronic Engineering Hanoi University of Industry Hanoi City, Vietnam
[3] Institute of Information Technology Vietnam Academy of Science and Technology Hanoi City, Vietnam
[4] Faculty of Electrical and Electronic Engineering Phenikaa University Hanoi City, Vietnam
[5] Graduate University of Science and Technology, VAST, Hanoi City, Vietnam
Correspondence: Duc-Nghia Tran, Email: nghiatd@ioit.ac.vn
Received: 28/07/2024, revised: 05/09/2024, accepted: 02/010/2024
Digital Object Identifier: 10.32913/mic-ict-research-vn.v2024.n2.1292

Abstract: At the moment, human physical activities can be detected and classified by activity recognition systems. One of the key issues in human activity recognition (HAR) systems is cost, speed, and accuracy. With the advancement of mobile devices and increasingly sophisticated microprocessors, along with the integration of various sensors including accelerometers, human activity recognition has become easier and faster. However, the accuracy of activity classification based on accelerometer data depends on many different factors, which can lead to potential deviations in results. Through various experiments, we have found that selecting optimal features is crucial for the performance of classification. In this paper, we propose a simple feature set that yields very promising results with an accuracy of up to 99%.

Keywords: *IoT, HAR, wearable technology, accelerometer, activity classification.*

Tiêu đề: **Một giải pháp IoT phân loại các hoạt động thể chất của con người dựa trên các cảm biến và thuật toán học có giám sát**

Tóm tắt: Hiện tại, các hoạt động thể chất của con người có thể được phát hiện và phân loại bằng các hệ thống nhận dạng hoạt động. Một trong những vấn đề chính trong các hệ thống nhận dạng hoạt động của con người (HAR) là chi phí, tốc độ và độ chính xác. Với sự tiến bộ của các thiết bị di động và bộ vi xử lý ngày càng tinh vi, cùng với sự tích hợp của nhiều cảm biến khác nhau bao gồm cả máy đo gia tốc, việc nhận dạng hoạt động của con người đã trở nên dễ dàng và nhanh hơn. Tuy nhiên, độ chính xác của phân loại hoạt động dựa trên dữ liệu máy đo gia tốc phụ thuộc vào nhiều yếu tố khác nhau, có thể dẫn đến độ lệch tiềm ẩn trong kết quả. Thông qua nhiều thử nghiệm khác nhau, chúng tôi thấy rằng việc lựa chọn các tính năng tối ưu là rất quan trọng đối với hiệu suất phân loại. Trong bài báo này, chúng tôi đề xuất một bộ tính năng đơn giản mang lại kết quả rất hứa hẹn với độ chính xác lên tới 99%.

Từ khóa: *IoT, HAR, wearable technology, accelerometer, activity classification.*

I. INTRODUCTION

The problem of HAR in general, and accelerometer-based activity recognition in particular, is proving to be highly significant with numerous applications in fields such as agriculture, healthcare, security, senior fall detection, industry [1]-[7], etc. By collecting data on user behavior and providing a range of engagement options, activity recognition technology allows systems to actively assist users in completing their activities [8]. Three common methodologies have been identified: wearable device sensor-based approach, environment-interaction sensor-based approach, and computer vision-based approach [9]-[10]. The vision-based technique uses cameras or movies to monitor changes in the surrounding environment and user activity [11]. However, there are drawbacks to employing security cameras, including their expensive cost, poor performance in low light, and privacy concerns for users [12]. In order to monitor user behaviors, sensors implanted in people or items that make up the surrounding environment are used in the environment-interaction sensor-based approach [13]. This system needs to be installed and pre-deployed, just like the computer vision-based method. The wearable sensor-based approach, in contrast to the previously described methods, makes use of body sensors, creating a wide range of possible applications in HAR [14]-[16]. As technology progresses, sensors are diversifying to improve identification rates and adjust to different scenarios. Whether used indoors or out, they don't require installation and are appropriate for any setting [17]. This approach allows for the wear of sensors on the human body in a number of locations, including the arm, wrist, thigh, front pocket, ankle, or foot [18]-[21]. The goal of this research is to take advantage of body-worn sensors' capacity to identify human states. The work of L. Bao et al. [19], who gathered data from two-axis accelerometer sensors worn at various points such as the arm, ankle, hip, wrist, and thigh among the study group, is one of the significant studies using numerous sensors to recognize human behavior. With 20 activities correctly classified, the Decision Tree (DT) classifier's accuracy was 84%. Nevertheless, drawbacks included the need for more sensors, high sample rates, and directionally oriented accelerometers. A. Wang et al. [9] examined the use of only accelerometer sensors, only gyroscopic sensors, and the simultaneous use of both. According to experimental findings, accelerometers offered superior discriminative information compared to gyroscopes, and combining the two sensor types improved classification performance. Compared to KNN's 87.8% overall accuracy, Naïve Bayes scored a higher 90.1% accuracy. The design of a medical device for old or recently recovered individuals is proposed by this study. The following are the paper's principal contents: - We look into using low-power microcontrollers with low-complexity algorithms. Because of its low computing cost and straightforward real-time implementation, the Random Forest (RF) technique is a great option. - We develop a real-time responsive, low-cost IoT activity recognition system. The system combines machine learning (ML) models, signal processing, and electronic circuits. Data gathering, preprocessing, feature extraction, direct classification on the microcontroller, and wireless transfer to the server are the steps in the process. The proposed method uses a minimal set of features, allowing the system to perform real-time recognition while still achieving high accuracy.

II. RESEARCH METHOD

1. Model of Activity Recognition

Supervised learning algorithms use a mapping function to create pairs of known (input, output) values and then predict the result or label of next input. Unsupervised learning, on the other hand, just uses input data without any predicted labels or results. A approach known as semi-supervised learning uses a lot of data, but only some of it is labeled. Furthermore, the system can choose the optimal course of action based on the present situation in order to maximize performance thanks to reinforcement learning models. To increase accuracy, supervised learning techniques will be used in this work. As illustrated in Figure 1, the overall approach to this HAR problem consists of three stages: data collection, model analysis, and activity recognition operations. The novelty is that we use a 3-axis accelerometer, which provides better performance and accuracy compared to the 2-axis accelerometer used by L. Bao et al. [19]. Acceleration data is collected along 3-axis (Ax, Ay, and Az) from the proposed system for activity classification in Stage 1 (data collection). The data streams are split up into manageable chunks in Stage 2. Here, all activity data is captured by moving a sliding window along the stream. Subsequently, each segment-created vector will have features that have been taken from the data. Selecting features to be used as the classifier's input is the next stage. Additionally, the characteristics chosen in the previous step will be trained to create the classification model at the last stage (deployment and evaluation). Classifiers have been gathered to determine activities based on the learned model.

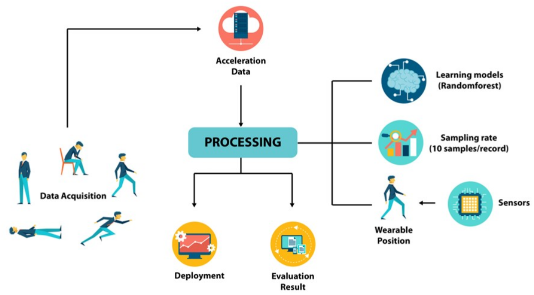
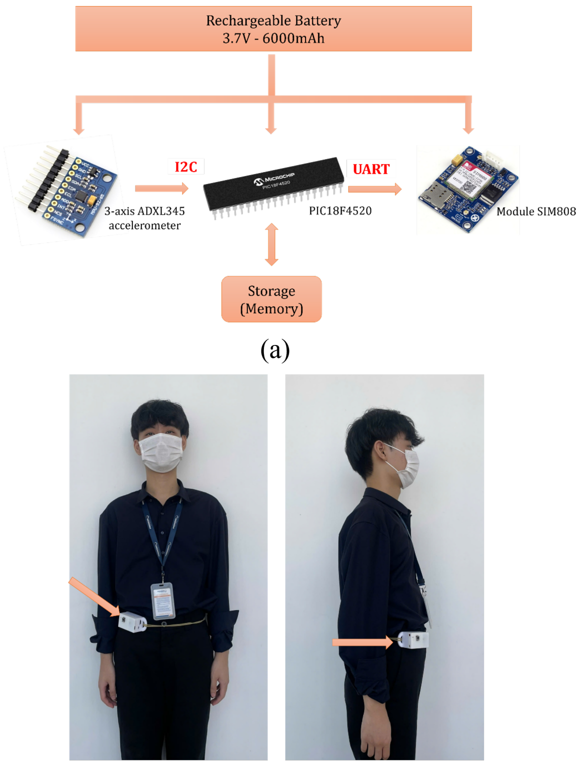


Figure 1. The classification state process

2. Information Gathering

To facilitate classification tasks, the proposed system combines a low-cost IMU sensor with a wireless network to send and receive data to the wearable device. The system proposed in this study uses a 3-DOF ADXL345 accelerometer to collect motion data. To ensure accurate activity measurement, the sensor parameters were configured with a 4g full scale, 128 LSB/g sensitivity, and a noise level of 150 μg. This setup allows for tri-axial data acquisition on the X, Y, and Z axes. The ADXL345 sensor is connected to the PIC18F4520 microcontroller via an I2C interface, while data transmission is handled by the ModuleSim module through UART communication with the MCU. Compared



(a)

(b)

Figure 2. The device (a) and the device attached to a volunteer (b).

with the 2-axis accelerometer used in the study by L. Bao et al. [19], 3-axis collection captures motion in all directions, offering a more complete and accurate representation of user activity, especially for detecting complex or multidimensional movements. Data will be sent from this gadget to a smartphone running Android OS. Figure 2 shows the proposed system structure. Asynchronous Receiver/Transmitter protocol to connect with the MCU. The gadget is powered by a 3.7V, 6000mAh rechargeable battery in this configuration. A Dell E6540 laptop (2.7 GHz processor and 8GB RAM) was used for our investigation. In order to gather data on daily activity, we conducted an experiment with 14 students, ages 18 to 22, heights of 1.55 to 1.8 m, and weights of 42 to 68 kg. We also recorded data with two older persons, ages 62 to 75, heights of 1.5 m and 1.66 m, and weights of 48 kg and 55 kg. Students wore the proposed gadget, which had a 50 Hz sampling frequency, around their waists. Four different states were recorded: walking, standing, sitting, and running. We apply the algorithm to this system as illustrated in Figure 1, and hardware components as in Figure 2(a). This research aims to develop optimized algorithms for low-performance, cost-effective microcontrollers (Tiny Machine Learning) for use in embedded systems and Internet-of-Things (IoT) devices.

Specifically, the algorithm is embedded into the device to enable real-time activity recognition. In this context, the microcontroller acted as the Central Processing Unit (CPU) of the embedded device, making the programming of wearable devices to recognize activities in real-time crucial. Real-time recognition required careful consideration of algorithmic complexity and memory constraints. As a result, machine learning algorithms like Random Forest (RF) are well-suited for deploying HAR on wearable devices in real-time. In this algorithm, decision trees (DTs) were constructed based on trained data, providing feature thresholds for creating binary DTs. The RF algorithm implementation followed these steps: during the setup phase, variables from the ADXL345 library were declared to define thresholds for distinguishing between motor and non-motor activities, set values for tap and double-tap detection, thresholds, free-fall time, and configured interrupts. In the loop phase, the model identified the ongoing activity, with thresholds derived from the training process. This process repeats every 5 seconds to deliver real-time results while ensuring low computational complexity.

3. Analysis of Features

Accelerometer data will be utilized to examine the features of activities after sensor data has been gathered. The data streams are first split up into manageable chunks that provide actionable information. Individuals carry out tasks with ease, and subsequent tasks influence one another. Furthermore, it can be difficult to define the precise limits of an activity, which is why data egmentation is required. The sliding window method is the method of data segmentation used in this article since it is easy to use and works well for real-time applications. It has been demonstrated that this method works well for differentiating between static (like standing and sitting) and periodic (like running and walking) activities. The sensor signal is split into time windows of a predetermined size in this instance. 14 people participated in the experiment by wearing the device around their waists (see Figure 2 for an example) and carrying out a predetermined list of tasks. In this study, volunteers wore sensors on their waists and performed four activities: standing naturally, sitting on a chair, jogging at a slow and steady pace, and normal walking. The number of activity observations with an 8-second window size (and a 50% overlap rate) is shown in Table I. There are 5239 observations in the retrieved dataset. The imbalance in sample sizes between sitting (273 samples) and standing (222 samples) compared to walking (3115 samples) and jogging (1629 samples) can be explained by the stability of these activities. Specifically, sitting and standing are static activities with minimal or no variation in the collected data,

Table I
ACTIVITY OBSERVATIONS COMPOSITION

Behavior pattern	Number of observations
Sitting	273
Standing	222
Waking	3115
Jogging	1629
Total	**5239**

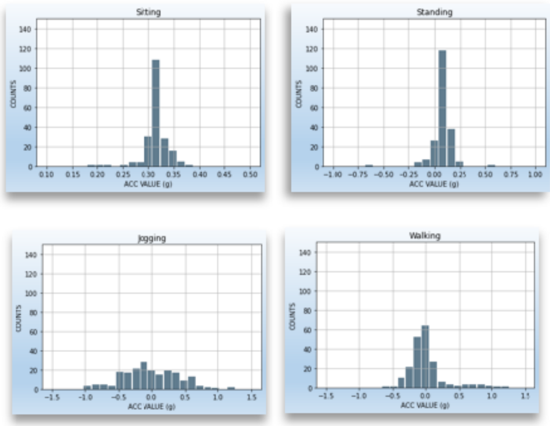


Figure 3. Histogram of 200 samples in X-axis

so fewer samples are needed to represent them adequately. In contrast, walking and jogging involve significant changes in the collected data due to their dynamic nature. The motion in these activities results in greater variations in acceleration, particularly across all 3-axis X, Y, and Z, requiring a larger volume of data to capture the full range of behavior changes. Thus, the study focused more on collecting data from activities with substantial variability to ensure accuracy in recognizing and classifying these actions. The dataset was split into a training set and a test set. Various ratios of training to test sets were tested, with the optimal ratio being 60% for training and 40% for testing. The training set, representing 60% of the original dataset, was randomly sampled from different subjects. The remaining 40% made up the test set, ensuring no overlap between the two sets. The proposed features were used to analyze the training dataset for model development.

4. Extraction of Features

Making the good feature selections to assist activities is essential to achieving good classification success. Prior to feature extraction, feature selection is done. A subset of the data for every activity was examined in order to choose characteristics. Figure 3 displays a subset of some data (about 200 samples) derived from the X-axis of accelerometer in order to determine associated attributes of each activity. Figure 3 illustrates how values for static states (Standing, Sitting) fall within a narrow range. For instance, sitting has about 200 sample values along the X-axis centered around (0.12g, 0.36g), while standing has about 150 values focused around ~ 0g on the axis ($1g = 9.8m/s^2$). In order to measure the data concentration level, distinguish dynamic states versus static states, and categorize static states among themselves, two features that can be used are the mean and median values. Furthermore, the value ranges of dynamic states—like walking and running are broader than those of static states. In order to ascertain the difference between the highest and lowest values of these states, the range has been selected. Then, we choose a set of features as shown in Table II below.

Table II
FEATURES DEFINITION (X-AXIS)

Feature	Formula	
Mean	$\mu(X_j) = \frac{1}{N}\sum_{i=1}^{N} x_i$	(1)
Standard deviation	$\sigma(X_j) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$	(2)
Median	$median(X_j) = \frac{x_{[\#N/2+1]} + x_{[\#N/2]}}{2}$, X_j was sorted	(3)
Range	$range(X_j) = \left[\min_{i=1}^{N}\{x_i\}, \max_{i=1}^{N}\{x_i\}\right]$	(4)
RMS (root mean square)	$RMS_{X_j} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	(5)

where: N : the total of data samples;
X_j: j^{th} record ;
x_i: i^{th} sample of X_j ;
$\mu(X_j)$: mean of X_j;
RMS_{X_j} : root mean square of X_j.
$\sigma(X_j)$: standard deviation of X_j;
min, max is the minimum, maximum value of X_j.
Note that the Y-axis and Z-axis features are similar.

5. Classification of Activities

The key to recognizing activities is the classifier. In addition to having a quick training period and excellent accuracy, classifiers frequently have to fulfill real-time demands. The training and classification procedure will use the feature set that was extracted in the preceding step as input. We used popular ML classification techniques as

Support Vector Machines (SVM), Gradient Boosting Decision Trees (GBDT), and k-Nearest Neighbors (KNN) via the Sklearn package. The performance of these classification models will be assessed and compared to RF (our proposed technique).

6. Evaluation indicators

Using a test dataset, the classification model's performance is frequently assessed. The confusion matrix, which evaluates the accuracy of the classifier by comparing real and expected outputs, is the most often used performance measurement technique. Four indicators including accuracy (acc), sensitivity (sen), Positive Predictive Value (PPV), and Negative Predictive Value (NPV) are utilized to improve recognizing capabilities.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{PPV} = \frac{TP}{TP+FP} \quad (3)$$

$$\text{NPV} = \frac{TN}{TN+FN} \quad (4)$$

where:
True Positive (TP): the model predicts correct that activity happens when it happened.
False Positive (FP)): an activity doesn't happen, but the device predicts it happened.
False Negative (FN): activity happens, but the device predicts different activity to happen.
True Negative (TN): the model predicts correct that activity doesn't happens when it doesn't happened.

III. RESULTS AND DISCUSSION

The process of classifying actions on real devices is conducted as follows: each action is tested for a period of 5-10 minutes, this process is continuous and there are changes in actions close to reality during the experiment. For example, changing from sitting to walking, changing from walking to jogging. Based on (1) (2), the accuracy and sensitivity of all classifiers are compared. With various window sizes (5 second, 8 second, 10 second, 12 second, 15 second), we tested all classifiers. For 8-second window size, the RF classifier exhibits the best performance. See Figures 4 and Figures 5. The data's confusion matrix displays the specific outcomes of applying the RF classifier. Most of the behavioral test samples in Table III exhibit reasonably distinct distinctions.
Table IV on our dataset displays all activity performance metrics. The train/test time for each algorithm as shown

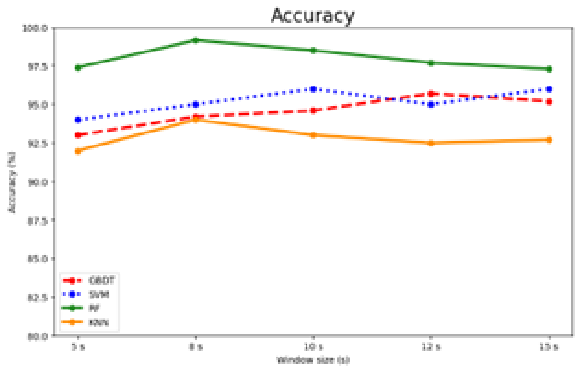


Figure 4. Sensitivity of public dataset

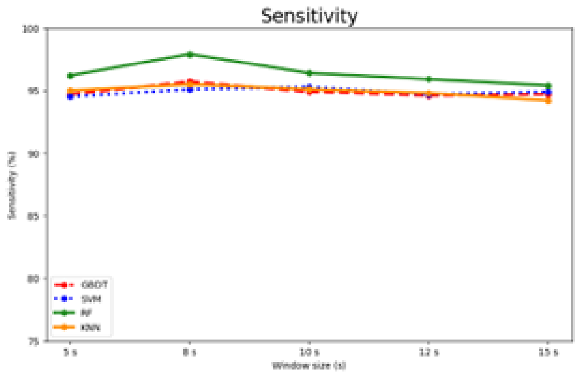


Figure 5. Sensitivity of the recorded dataset

in Table V. Numerous studies select a large number of variables in an effort to increase the rate of activity identification. With a comparatively high recognition performance, the current study merely employed a straightforward and efficient set of 5 statistical features along with the ideal 8-second sliding window size. A comparison of the effectiveness of the proposed classification model with the research of P. N. Huu [21]. The accuracy in this study is better when classifying standing, sitting, walking and jogging activities,

Table III
CONFUSION MATRIX

Observed behavior	Predicted behavior				Total
	Sitting	Standing	Waking	Jogging	
Sitting	**261**	12	0	0	273
Standing	0	**221**	1	0	222
Waking	4	33	**3066**	12	3115
Jogging	0	0	27	**1602**	1629
Total	265	266	3094	1614	5239

Table IV
PERFORMANCE OF THE MODEL USING INDICES

Behavior pattern	Acc	Sen	PPV	NPV
Siting	99,69%	95,60%	98,49%	99,91%
Stading	99,12%	99,54%	83,08%	99,10%
Waking	98,53%	98,42%	99,09%	98,68%
Jogging	99,25%	98,34%	99,25%	99,66%

Table V
TIME FOR TRAIN/TEST

Algorithm	Time (s/activity)	
	Train (60%)	Test (40%)
Gradient Boosting Decision Tree	14.47	0.019
SVM	0.17	0.14
Random Forests	2.93	0.079
Kneighbor	0.009	0.05

achieving about 99% compared to 93,3% for P. N. Huu [21]. However, they classified more activities (nine upper body activities) than our study. They also tested a more complex algorithm that combined multiple different lassification algorithms. The comparison of accuracy between the study by L. Bao et al. [19] and our research shows a significant difference. In L. Bao et al. study, the accuracy for activities was 89,71% for walking, 94,78% for sitting, 95,67% for standing still, and 87,68% for running. In contrast, our research achieved considerably higher accuracy: 98,53% for walking, 99,69% for sitting, 99,12% for standing still, and 99,25% for running. This improvement is largely attributed to the use of a three-axis accelerometer worn on the waist, which provides comprehensive coverage of all four activities.

IV. CONCLUSION

We have effectively integrated low-complexity computational algorithms onto microcontroller units that consume minimal power. According to test findings, the RF classifier outperforms other algorithms when an 8-second window size is used. The random forest approach has low processing overhead and can be implemented in real time. A basic set of five features can be used to accurately classify the daily activities of various persons. One of the main problems with assistive technology is user acceptance. The applications of computer vision techniques are very promising. However, privacy considerations might make computer vision-based systems less acceptable in this situation; elderly people might not want their photos to be followed and stored. Reducing stigma is essential for systems that help the elderly. When others are aware that they are utilizing these devices, people do not feel at ease. Due to its easy concealment by clothing, the device worn at the waist (with the sensor within) satisfies this criteria.

ACKNOWLEDGEMENT

This research is funded by Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number: 02/2022/TN.

REFERENCES

[1] M. A. Khan et al., “A Fused Heterogeneous Deep Neural Network and Robust Feature Selection Framework for Human Actions Recognition,” *Arab J Sci Eng*, Jul. 2021.

[2] S. Chernbumroong, S. Cang, A. Atkins, and H. Yu, “Elderly activities recognition and classification for applications in assisted living,” *Expert Systems with Applications*, vol. 40, no. 5, pp. 1662–1674, 2013.

[3] K. K. B. Peetoom, M. A. S. Lexis, M. Joore, C. D. Dirksen, and L. P. De Witte, “Literature review on monitoring technologies and their outcomes in independently living elderly people,” *Disability and Rehabilitation: Assistive Technology*, vol. 10, no. 4, pp. 271–294, 2015.

[4] P. Pierleoni, A. Belli, L. Palma, M. Pellegrini, L. Pernini, and S. Valenti, “A High Reliability Wearable Device for Elderly Fall Detection,” *IEEE Sensors Journal*, vol. 15, no. 8, pp. 4544–4553, 2015.

[5] S. E.-R. Pham Van Thanh, Duc-Tan Tran, Dinh-Chinh Nguyen, Nguyen Duc Anh, Dang Nhu Dinh and K. Sandrasegaran, “Development of a Real-Time, Simple and High-Accuracy Fall Detection System for Elderly Using 3-DOF Accelerometers,” *Arabian Journal for Science and Engineering*, pp. 3–4, 2018.

[6] N. T. T. Hong, et al., “A Low-cost Real-time IoT Human Activity Recognition System Based on Wearable Sensor and the Supervised Learning Algorithms,” *Measurement*, Vol. 218, 113231, 2023.

[7] A. Jain and V. Kanhangad, “Exploring orientation and accelerometer sensor data for personal authentication in smartphones using touchscreen gestures,” *Pattern Recognition Letters*, vol. 68, pp. 351–360, 2015.

[8] N. N. Diep, C. Pham, and T. M. Phuong, “A classifier based approach to real-time fall detection using low-cost wearable sensors,” *in Proceedings of the Fifth Symposium on Information and Communication Technology - SoICT ’14*, Hanoi, Viet Nam, 2014.

[9] A. Wang, G. Chen, J. Yang, S. Zhao, and C. Y. Chang, “A Comparative Study on Human Activity Recognition Using Inertial Sensors in a Smartphone,” *IEEE Sensors Journal*, vol. 16, no. 11, pp. 4566–4578, 2016.

[10] S. Khan et al., “Human Action Recognition: A Paradigm of Best Deep Learning Features Selection and Serial Based Extended Fusion,” *Sensors*, vol. 21, no. 23, 2021.

[11] F. Marquis-Faulkes, S. J. McKenna, A. F. Newell, and P. Gregor, “Gathering the requirements for a fall monitor

using drama and video with older people," *Technology and Disability*, vol. 17, no. 4, pp. 227–236, 2005.
[12] M. A. Khan, Y.-D. Zhang, S. A. Khan, M. Attique, A. Rehman, and S. Seo, "A resource conscious human action recognition framework using 26-layered deep convolutional neural network," *Multimed Tools Appl*, vol. 80, no. 28–29, pp. 35827–35849, Nov. 2021.
[13] M. Sundholm, J. Cheng, B. Zhou, A. Sethi, and P. Lukowicz, "Smart-mat: Recognizing and counting gym exercises with low-cost resistive pressure sensing matrix," *UbiComp 2014 - Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 373–382, 2014.
[14] C. Zhu and W. Sheng, "Wearable sensor-based hand gesture and daily activity recognition for robot-assisted living," *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, vol. 41, no. 3, pp. 569–573, 2011.
[15] A. Mannini, S. S. Intille, M. Rosenberger, A. M. Sabatini, and W. Haskell, "Activity Recognition Using a Single Accelerometer Placed at the Wrist or Ankle," *Medicine & Science in Sports & Exercise*, vol. 45, no. 11, pp. 2193–2203, 2013.
[16] J. Pärkkä, M. Ermes, P. Korpipää, J. Mäntyjärvi, J. Peltola, and I. Korhonen, "Activity classification using realistic data from wearable sensors," *IEEE Transactions on Information Technology in Biomedicine*, vol. 10, no. 1, pp. 119–128, 2006.
[17] M. Ahmed et al., "Real-Time Violent Action Recognition Using Key Frames Extraction and Deep Learning," *Computers, Materials & Continua*, vol. 69, no. 2, pp. 2217–2230, 2021.
[18] N. Ravi, N. Dandekar, P. Mysore and M. L. Littman, "Activity recognition from accelerometer data," *Lecture Notes in Networks and Systems*, vol. 43, pp. 317–329, 2019.
[19] L. Bao and S. S. Intille, "Activity Recognition from User-Annotated Acceleration Data BT-UbiComp 2002: Ubiquitous Computing," *Ubiquitous Computing*, vol. 3001, no. Chapter 1, pp. 1–17, 2004.
[20] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," *ACM SIGKDD Explorations Newsletter*, vol. 12, no. 2, pp. 74–82, 2011.
[21] P. Nguyen Huu, N. Nguyen Thi and T. P. Ngoc, "Proposing Posture Recognition System Combining MobilenetV2 and LSTM for Medical Surveillance", *IEEE Access*, vol. 10, pp. 1839-1849, 2022.

Vu Thi Thuong Graduated with a Master's degree in Computer Science in 2009 at the Military Technical Academy. Currently a lecturer at the Faculty of Information Technology and Communications, Phuong Dong University. Research field: Machine learning methods to improve signal measurement, using accelerometers and machine learning algorithms to serve the problem of identifying and classifying behavior.
Email: thuongvt@dhpd.edu.vn

Thu Nguyen Thi received Ph.D. degree in Electronic Engineering from Le Quy Don Technical University, Vietnam in 2018. Dr. Nguyen research interests are in the areas of space-time signal processing for communications such as MIMO, spatial modulation and cooperative communications, artificial neural networks.
Email: thunt@haui.edu.vn.

Duc-Ngia Tran Received the Ph.D. degree from Sorbonne Paris Cité, France. In his thesis, he focuses on signal processing of EPR spectra for in vivo experiments. He is a Researcher with the Institute of Information Technology (IOIT), Vietnam Academy of Science and Technology (VAST). His research interests include mathematics and signal processing, electron paramagnetic resonance (EPR), parameter estimation, and data analysis.
Email: nghiatd@ioit.ac.vn

Nguyen Nhu Son Received the Ph.D. degree in Computer Science from The University of Queenslnad, Australia, in 2007. He is currently a Vice Chair of Scientific Council, Head of Department at Institute of Information Technology (IOIT) - Vietnam Academy of Science and Technology. His research interests include artificial intelligence, data mining, soft computing, and fuzzy computing. .
Email: nnson@ioit.ac.vn

Tran Duc Tan Received BTech degree in electronics engineering from College of Technology, Hanoi, Vietnam in 2002 and MTech degree in electronics engineering from College of Technology, Hanoi, Vietnam in 2005 and Ph.D. degree in electronics engineering from electronics engineering VNU University of Engineering and Technology, Hanoi, Vietnam. He is currently Vice Dean of Faculty of Electrical and Electronics Engineering, PHENIKAA University. His current research interest is in signal processing for biomedical imaging.
Email: tan.tranduc@phenikaa-uni.edu.vn.