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Real-time sleep posture classification using wearable accelerometers and machine learning models

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ABSTRACT

Sleep posture plays a critical role in sleep quality and health, influencing conditions such as sleep apnea. Accurate classification of sleep postures is essential for diagnosing and treating sleep-related disorders. The sleep posture can be detected by using wearable acceleromter. This paper presents an realtime classification system for four sleep postures by integrating accelerometer data with a machine learning (ML) model. The proposed system was tested with various ML models, including decision trees (DT), random forest (RF), K-nearest neighbors (KNN), support vector classifier (SVC), and logistic regression (LR), across multiple performance metrics. The results demonstrate that the LR model, when combined with accelerometer data, significantly outperforms other methods, achieving a classification accuracy of 91%. This paper also discusses the system's potential for real-time deployment on embedded devices, contributing to advancements in sleep posture monitoring.

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1. INTRODUCTION

Sleep is a fundamental physiological process that is essential for maintaining physical and mental well-being. A critical factor influencing sleep quality and overall health is sleep posture, which affects physiological functions such as respiration, circulation, and musculoskeletal alignment [1]. Poor sleep posture has been linked to various health conditions, including obstructive sleep apnea (OSA), acid reflux, and chronic musculoskeletal pain [2]. Consequently, accurate classification of sleep posture is crucial for diagnosing and managing sleep-related disorders, optimizing therapeutic interventions, and improving sleep quality [3]–[5].

Traditionally, sleep posture monitoring has relied on polysomnography (PSG), which is considered the gold standard for sleep analysis [6]. PSG involves recording multiple physiological signals, including brain activity, eye movements, muscle activity, and respiratory patterns, within a controlled sleep laboratory environment. While effective, PSG is expensive, intrusive, and impractical for long-term monitoring outside clinical settings [7]. As a result, alternative methods utilizing non-invasive wearable sensors, such as accelerometers and gyroscopes, have been explored for sleep posture classification [8].

Wearable accelerometers offer a convenient and cost-effective approach to continuous sleep posture monitoring. These sensors detect changes in body orientation and movement by measuring acceleration along multiple axes [9]–[12]. Advances in machine learning (ML) have further enhanced the capability of accelerometer-based systems by enabling automated and real-time classification of sleep postures with high accuracy [13]. Various ML algorithms, including decision trees (DT), random forest (RF), K-nearest nighbors (KNN), support vector classifier (SVC), and logistic regression (LR), have been applied to analyze accelerometer data and identify distinct sleep postures [14]–[16].

Recent studies have demonstrated the potential of wearable devices in sleep monitoring applications. In [17], a patch-type sensor with a 3-axis accelerometer was used to develop a sleep posture estimation algorithm, successfully classifying five sleep and non-sleep postures. Meanwhile, Wang *et al.* [18] explored automatic sleep position detection with a single neck-worn accelerometer, overcoming suboptimal placement challenges to support multimodal healthcare applications, using models like DT, extra-trees (ET) classifier, and long short-term memory neural networks (LSTM-NN). Expanding on these advancements, Breuss *et al.* [19] introduced a novel sleep monitoring system integrating a three-axis accelerometer and a pressure sensor to assess sleep quality based on key physiological parameters, such as non-REM sleep duration and apneic episodes. A 20-day experiment with three participants validated the system's ability to provide effective, non-intrusive sleep quality analysis.

This paper addresses remaining challenges by proposing a real-time sleep posture classification system utilizing wearable accelerometers and ML models. Unlike many prior works relying on complex or computationally demanding methods, we demonstrate that LR, a lightweight yet effective model, can achieve the highest classification accuracy of 91%, outperforming more complex classifiers. Moreover, the system is designed with real-time deployment in mind, making it practical for integration into wearable or embedded devices.

The remainder of this paper is organized as follows: section 2 describes the methodology, including data collection, preprocessing, feature extraction, and ML model implementation. Section 3 presents experimental results and performance evaluation. Section 4 discusses potential applications and limitations, followed by conclusions and future research directions in section 5.

2. METHOD

2.1. Data collection and pre-processing

The proposed system utilizes a wearable device equipped with an accelerometer, placed on the abdomen of the subject (see Figure 1). In this research, the ADXL345 accelerometer is utilized to measure both static and dynamic human movement. This compact, low-power, 3-axis accelerometer features signal-conditioned voltage output, making it suitable for various applications. It can detect static acceleration for tilt sensing as well as dynamic acceleration caused by motion, shock, or vibration. The device offers selectable bandwidths ranging from 0.5 Hz to 200 Hz across all axes. The algorithms for calculating acceleration along an axis are as (1):

$$A_i = \frac{\left[\frac{V_i}{1024} \times R_{ADC-0_i}\right]}{S_i}, \quad i = X, Y, Z \tag{1}$$

where A_i represents the acceleration value in the i^{th} direction $i = X, Y, Z$; V_i is the sampled value of the i axis; R_{ADC} denotes the reference voltage; O_i is the 0 g voltage after a simple calibration of the i axis; and S_i is the sensitivity of the accelerometer for the i axis [19].

Table 1 shows an example of samples along three axes (X, Y, and Z) in lying position with acceleration values. Data were collected using the ADXL345 accelerometer placed on the abdomen of participants. The dataset consisted of approximately 3000 samples (balanced across the four postures: supine, prone, left lateral, and right lateral as shown in Table 2), with each posture recorded continuously for 60 seconds per subject at a sampling frequency of 50 Hz. Data were collected from 15 volunteers aged between 19–24 years, ensuring representation across different body sizes and weights, although the dataset is still relatively limited in terms of diversity and duration compared to real-world scenarios. This constraint is acknowledged as a potential limitation in terms of generalization to broader populations. First, data is filtered using a low-pass filter to remove high-frequency noise and artifacts caused by sudden movements [20]. Missing values or outliers are handled using median filtering. The data is then resampled to a uniform frequency to ensure consistency across different recording sessions.

Table 1. An observation sample along three axes X, Y, and Z (lying position)

Acceleration in X (g)	Acceleration in Y (g)	Acceleration in Z (g)
0.0123	-0.0035	9.8102
0.0089	0.0021	9.8157
-0.0056	-0.0043	9.8073
0.0017	0.0009	9.8125
-0.0024	-0.0011	9.8096
0.0032	0.0028	9.8131

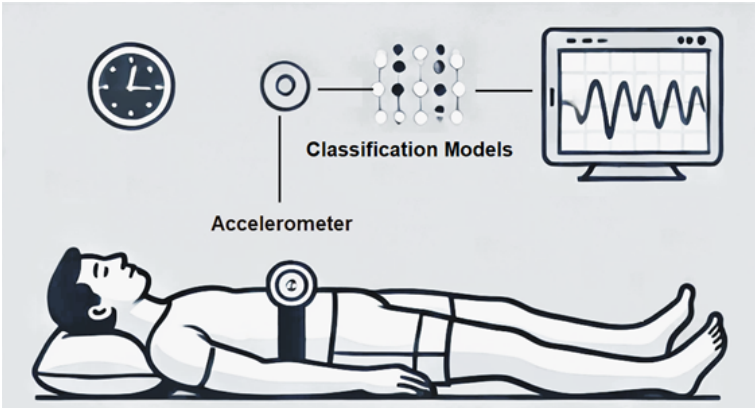


Figure 1. Experimental configuration with a volunteer positioned supine and equipped with the abdominal sensing device

Table 2. Definition of sleep postures

Sleep posture	Description	Expected acceleration characteristics (X, Y, Z axes)
Prone (face down)	Lying on the stomach with the head turned to one side.	X: moderate, Y: low, Z: high (chest pressure on sensor)
Lateral left	Lying on the left side with arms and legs positioned freely.	X: high, Y: moderate, Z: lower than supine/prone
Lateral right	Lying on the right side in a similar manner to the left.	X: hgh, Y: moderate, Z: lower than supine/prone
Supine (face up)	Lying on the back with arms and legs relaxed.	X: low, Y: low, Z: high (gravity along Z-axis)

The data is then segmented into overlapping sequences using a rectangular windowing [21]. A fixed sequence length is defined, and each segment is extracted with a 40% overlap ratio. This method is crucial for capturing temporal dependencies in movement patterns and providing contextual information to the models. The dataset is divided into training and validation sets using Scikit-learn's *train_test_split* function at the ratio 4:1, ensuring that models are trained on one subset and evaluated on another to prevent overfitting. In this study, we focus on building a very fast classification device, thus, we need only four features (in the time domain) as the input of the classification as follows:

- The raw accelerometer data (X, Y, Z) is segmented into overlapping time windows of a fixed length. This ensures that the modjels can capture temporal patterns in movement, which are crucial for distinguishing different sleep positions.
- Root sum square (RSS): $RSS = \sqrt{X^2 + Y^2 + Z^2}$. The RSS feature helps reduce noise and provides a compact representation of motion.

Each extracted feature (X, Y, Z, and RSS) is scaled to a fixed range (e.g., [0,1]) using MinMax normalization. This prevents models from being biased toward larger numerical values and ensures consistent feature importance.

Additional statistical features such as mean, standard deviation, skewness, and entropy were initially considered; however, preliminary experiments indicated that they did not provide significant performance improvement compared to the selected four time-domain features, while increasing computational complexity. Therefore, to maintain model simplicity and ensure real-time feasibility on resource-constrained embedded devices, only the most discriminative and computationally efficient features (X, Y, Z, and RSS) were retained.

To ensure fair comparison and optimize performance, each ML model was tuned using a grid search approach combined with validation on the training set. For the DT and RF classifiers, parameters such as tree depth, number of estimators, and minimum samples per split were adjusted to balance complexity and generalization. For KNN, the number of neighbors k was varied, and distance metrics were evaluated to identify the most effective configuration. The support vector machine (SVM) was tuned by experimenting with different kernel functions (linear, polynomial, and radial basis function) and adjusting the penalty parameter C. For LR, the regularization strength was optimized through variation of the inverse regularization parameter C, ensuring stable convergence without overfitting. In practice, parameter tuning was performed iteratively: models were first trained with default Scikit-learn parameters, followed by systematic adjustments within reasonable ranges. The final parameters were selected based on validation accuracy and consistency of performance across multiple runs. While exhaustive search methods such as K-fold cross-validation grid search could provide more rigorous optimization, the simpler tuning strategy adopted here was sufficient to achieve robust performance, aligning with the study's goal of real-time implementation on resource-constrained devices.

2.2. Comparative models

To validate the effectiveness of the real-time classification models, we investigate some typical classifiers, including DT, RF, KNN, SVM, and LR [22]-[25]. Each classifier is tuned, and trained using above features and tested on the test dataset to determine the most suitable model for sleep posture classification (see Figure 2).

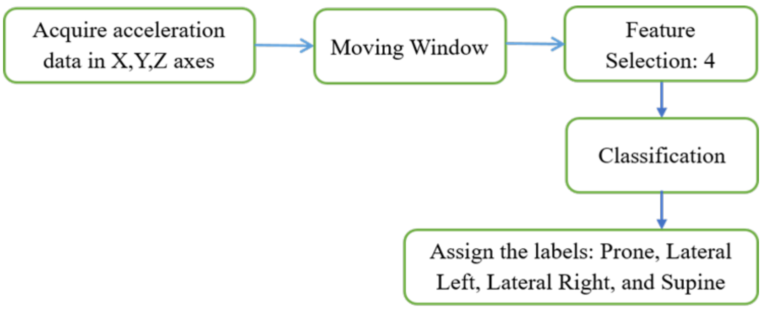


Figure 2. The process of classification of sleep posture

Each model was evaluated using the same dataset, and their performance was assessed based on confusion matrices and accuracy. The formula of accuracy is given by (2):

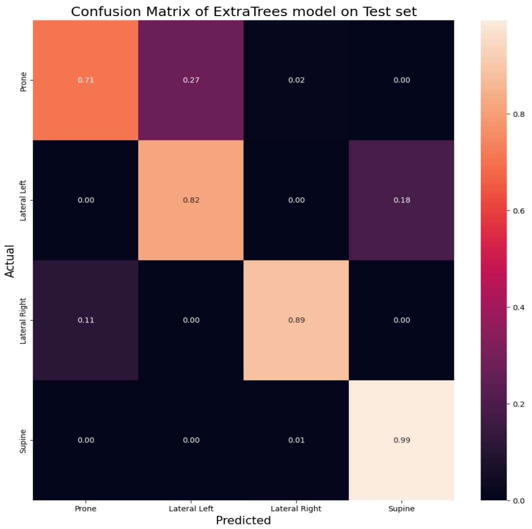
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

where TP (true positive) refers to the number of instances where the positive class is correctly predicted, TN (true negative) represents the number of instances where the negative class is correctly predicted, (FP (false positive) denotes the number of instances where the negative class is incorrectly predicted as positive, and FN (false negative) indicates the number of instances where the positive class is incorrectly predicted as negative.

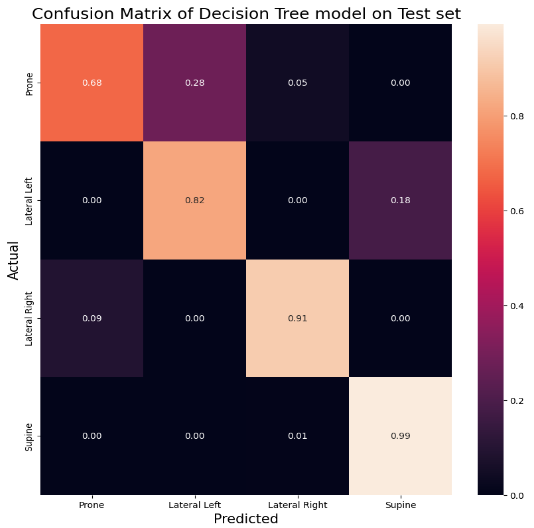
In line with the issues raised in the introduction—namely the need for accurate yet computationally efficient sleep posture classification methods suitable for wearable deployment—the results section is structured to directly address these gaps. First, we evaluate multiple ML models (DT, RF, KNN, SVC, and LR) using standardized performance metrics, allowing a comparative analysis of accuracy and robustness. This responds to the lack of systematic comparisons across lightweight and complex classifiers reported in prior studies. Second, by implementing LR on a microcontroller platform, we assess real-time feasibility, thereby addressing the challenge of translating high-accuracy methods into practical, embedded solutions. Finally, confusion matrices and detailed performance analyses are presented to interpret classification strengths and weaknesses, particularly between similar postures (e.g., lateral left vs. lateral right), highlighting both current capabilities and areas requiring further research.

3. RESULTS

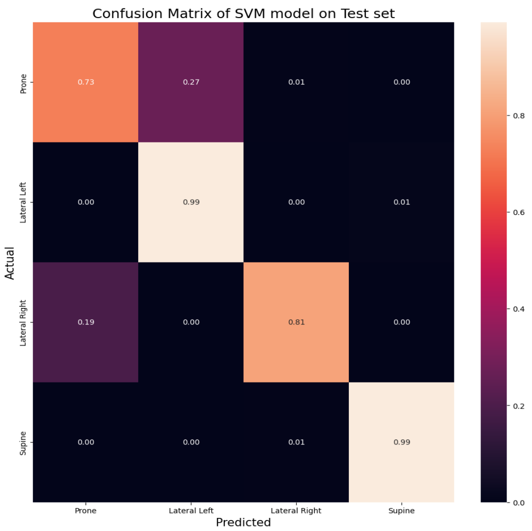
To clearly illustrate the performance of different classifiers, confusion matrices are presented in Figure 3. Specifically, Figure 3(a) shows the results obtained from the ET classifier, while Figure 3(b) corresponds to the DT classifier. Figure 3(c) presents the SVM results, and Figure 3(d) displays the RF classifier performance. These subfigures highlight the classification accuracy and potential misclassifications across the four sleep postures, allowing a direct comparison of the models. As observed from these confusion matrices, all models demonstrate reasonable classification capability; however, LR achieves superior accuracy with fewer misclassifications, particularly in distinguishing between similar postures such as lateral left and lateral right.



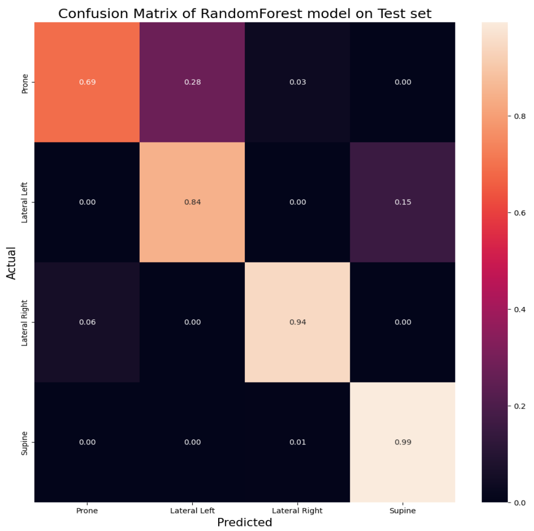
(a)



(b)



(c)



(d)

Figure 3. Confusion matrices of the tested models on the test set: (a) ET, (b) DT, (c) SVM, and (d) RF

The comparative analysis in Table 3 highlights that LR achieved the highest overall performance among the evaluated classifiers, with an accuracy of 91%, precision of 91.7%, recall of 90.8%, and F1-score of 90.7%. These results are noteworthy because LR is a relatively simple and computationally efficient model, yet it outperformed more complex algorithms such as RF (accuracy: 86.5%) and SVM (accuracy: 88%).

This finding suggests that for the given dataset—characterized by time-domain accelerometer features (X, Y, Z, and RSS) with appropriate normalization—linear decision boundaries are sufficient to separate the four sleep postures effectively. The superior performance of LR may also stem from the careful preprocessing steps, including noise filtering, balanced sampling, and normalization, which reduced the risk of overfitting and emphasized feature consistency.

Table 3. Results of classifier

Parametes name	ET	DT	SVM	RF	LR
Accuracy	0.853	0.85	0.88	0.865	0.91
Precision	0.858	0.853	0.886	0.87.4	0.917
Recall	0.853	0.848	0.878	0.867	0.908
F1-score	0.85	0.846	0.877	0.864	0.907

On the other hand, ensemble methods such as ET and RF, despite their robustness to noise, did not surpass LR. This could be attributed to the relatively small and well-structured dataset, where the added complexity of ensemble models did not yield significant advantages. Similarly, KNN showed the lowest accuracy (83%), likely due to its sensitivity to noise and reliance on local neighborhood structures, which may not generalize well across overlapping posture signals.

These results emphasize that model simplicity can be a strength in real-time wearable applications, where computational efficiency and resource constraints are critical. LR offers a favorable trade-off between accuracy and efficiency, making it particularly suitable for embedded deployment. Nevertheless, the marginal differences in performance between models highlight opportunities for further optimization, such as integrating temporal features or hybrid approaches that balance lightweight computation with improved robustness to posture transitions and noise.

Implement LR on a microcontroller: For efficient implementation (see Figure 4), the microcontroller should support floating-point operations or at least integer multiplication for approximating exponentials (used in the logistic function). Since a trained LR model is mathematically represented as (3):

$$P(y=i) = \frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+b_3x_3+b_4x_4)}} \tag{3}$$

where:

- P(y=i) is the probability that the posture belongs to class i (i=1,2,3,4).
- b_0 is the bias (intercept term).
- b_1,b_2,b_3,b_4 are the model coefficients (weights).
- x_1,x_2,x_3,x_4 are the input sensor features (mentioned in previous section).

The sigmoid function is computationally expensive due to the exponential operation, so we approximate it using a lookup table or Taylor series for efficiency.

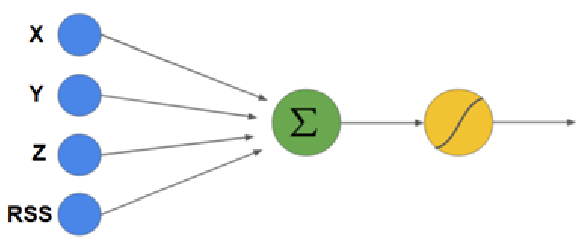


Figure 4. Implementation of LR on a microcontroller

4. DISCUSSION

4.1. Key findings and limitations

Consistent with the objectives outlined in the introduction, this study sought to develop a lightweight, real-time posture classifier for embedded systems. The results validate this approach, demonstrating that LR achieves 91% accuracy while maintaining a computational footprint suitable for microcontrollers. The findings of this study provide strong evidence that wearable accelerometers, when combined with appropriate ML models, can enable real-time classification of sleep postures with high accuracy. The proposed system demonstrates the feasibility of using simple yet effective ML techniques for practical sleep posture monitoring. By providing continuous posture monitoring without requiring expensive and intrusive PSG, this system offers a cost-effective and user-friendly alternative for long-term sleep assessment. Furthermore, the findings suggest that LR, a relatively simple ML model, can outperform more complex classifiers such as SVM and DT when trained on appropriately preprocessed accelerometer data. The achieved classification accuracy of 91% indicates that sleep posture variations can be effectively captured through motion-based feature extraction. This supports the idea that deep learning models, while promising in some contexts, may not always be necessary for accurate classification, especially when computational efficiency and real-time processing are required.

While the proposed system demonstrates promising results under controlled conditions, several real-world constraints must be considered. In practice, wearable accelerometers are susceptible to sensor noise and signal artifacts caused by involuntary movements, changes in clothing pressure, or device displacement during sleep. Such disturbances may reduce classification accuracy and require additional filtering or adaptive calibration. Another challenge is posture transition detection, as the system primarily targets static postures. Transitional states or micro-adjustments—common during natural sleep—may lead to ambiguous signals that fall outside the trained categories, highlighting the need for more sophisticated temporal modeling.

The system also faces limitations regarding scalability and generalizability. The current design assumes a single user with a fixed sensor placement on the abdomen. In real-world applications, variability in sensor positioning, body type, and sleeping habits across users could significantly affect performance. Moreover, the system is not designed to monitor multiple users simultaneously, which restricts its use in shared sleeping environments or clinical wards. Addressing these issues would require developing adaptive algorithms that account for inter-user variability and robustness to sensor misplacement.

When comparing with advanced approaches, such as deep learning models (e.g., convolutional neural networks, recurrent neural networks) [26], it is likely that these architectures could achieve higher accuracy, especially if trained on a large and diverse dataset. Deep learning models are capable of capturing nonlinear dependencies and complex temporal dynamics, which could improve posture transition detection and robustness against noise. However, they are computationally intensive and less practical for real-time deployment on embedded devices with limited resources. By contrast, the use of LR in this study strikes a favorable balance between accuracy and efficiency, making it suitable for lightweight, real-time applications, albeit with some trade-offs in flexibility and scalability.

4.2. Clinical translation and practical implications

The proposed real-time sleep posture classification system has the potential to support several clinically meaningful applications. One important application is its role as a home-based preliminary screening tool for posture-dependent sleep disorders, particularly OSA. Because body posture significantly influences airway obstruction in many OSA patients, continuous and unobtrusive monitoring of sleep posture can help identify individuals whose symptoms worsen in the supine position, enabling clinicians to decide whether further diagnostic procedures such as PSG are required.

Another important application of the system is monitoring therapy adherence and effectiveness. For patients undergoing positional therapy, continuous positive airway pressure (CPAP) adjustment, or behavioral interventions, objective records of nightly posture patterns can reveal whether prescribed recommendations are being followed. Over time, the analysis of posture dynamics may also provide insights into the effectiveness of treatment and support timely clinical adjustments.

The system can also assist clinicians by generating automated and interpretable summary reports. These reports may include information such as nightly posture distribution, frequency and duration of specific postures, and posture transition patterns. Such summarized data can help clinicians quickly identify behavioral trends and abnormal posture habits, thereby supporting more informed patient management.

Despite these promising applications, several limitations and challenges remain before clinical deployment. The current evaluation was conducted under controlled conditions with a modest sample size, so larger cohort studies are necessary to validate robustness across diverse populations and real-world sleeping environments. Future work should also include multi-center trials, integration with additional physiological signals (e.g., respiratory effort, heart rate variability, oxygen saturation, and snoring), and consideration of long-term usability, comfort, sensor calibration, and data privacy.

5. CONCLUSION

This study successfully demonstrates a real-time sleep posture classification system that integrates accelerometer data with ML techniques. The results indicate that traditional ML models, particularly LR, can achieve high classification accuracy with minimal computational demands. While challenges such as dataset generalizability, sensor placement variability, and posture transition detection remain, the findings provide a strong foundation for further research and development. Future research should therefore focus on expanding the dataset with more diverse participants and conducting long-term real-world experiments to validate system performance. Integrating additional physiological or environmental sensors, developing adaptive or personalized ML models, and improving robustness to sensor variability may further enhance classification accuracy and reliability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Duc-Tan Tran		✓							✓	✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal Analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, Nguyen Thi Thu, upon reasonable request.

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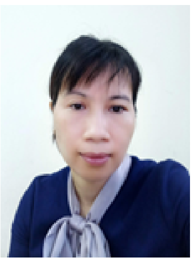

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