

Human Activity Recognition Using Machine Learning in Wireless Body-Area Networks

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Abstract—This work evaluates whether the Bluetooth Low Energy (BLE) Received Signal Strength Indicator (RSSI) alone can support human-action recognition (HAR) in a star-topology Wireless Body-Area Network (WBAN). Nine participants performed three activities (standing, walking, and sitting) while wearing a chest-mounted central node and four peripheral nodes on the wrists and ankles. RSSI streams were segmented into 10 s windows; from each window, fourteen statistical descriptors (e.g., mean, variance, percentiles) were extracted. Six conventional classifiers (k-NN, SVM, Random Forest, Logistic Regression, Naïve Bayes, and Gradient Boosting) were evaluated using 30 random seeds. The Gradient-Boosting model achieved the highest accuracy, $93\% \pm 1.46$. These demonstrate that RSSI-based features from only two sensors provide sufficient information for low-complexity accurate HAR in a WBAN.

Keywords—HAR, RSSI, On-Body Radio Channel, Machine Learning, Wearable IoT, BLE, WBAN.

I. INTRODUCTION

Human Activity Recognition (HAR) refers to the recognition of movement behavioral patterns by analyzing human activity signals, has become a cornerstone technology for a wide spectrum of applications ranging from health monitoring and assisted living to occupational safety and smart-environment control [1]. HAR methods are generally divided into four sensor-based categories: non-visual sensors [2], visual-based sensors [3], context-aware systems [4], and hybrid approaches [5]. Each category uses distinct modalities to capture and analyze human actions, providing specific benefits while addressing particular challenges of activity detection. Recognizing the advantages and constraints of each sensor type is essential for designing effective HAR solutions suited to a wide range of applications and environments.

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Traditionally, HAR systems rely on rich multimodal sensor suites accelerometers, gyroscopes, depth cameras, or radio-frequency devices mounted on the body or embedded in the environment [6]. While these sensor-heavy approaches can achieve high recognition rates, they also introduce practical drawbacks such as increased power consumption, higher device cost, and reduced user comfort.

To classify human activities, both deep-learning techniques and traditional machine-learning (ML) approaches can be employed. Convolutional neural networks (CNNs) and hybrid CNN-LSTM architectures are capable of learning discriminative representations directly from raw sensor streams, whereas transformers and graph neural networks (GNNs) [7] capture long-range temporal dependencies and exploit the spatial topology of multiple body-mounted sensors. Nevertheless, these models demand extensive labeled datasets, considerable computational power, and substantial memory resources, rendering them impractical for wireless body area networks (WBAN) that rely on Bluetooth Low Energy (BLE) and operate on resource-constrained edge devices. Consequently, the most feasible solution is to segment the sensor signals into short windows, extract a compact set of temporal and spectral features, and classify the activities using conventional machine-learning algorithms. This strategy yields adequate performance while preserving the autonomy of the sensor network and maintaining the simplicity of the edge node.

In this work we explore a minimalist alternative: recognition of human activities using only the Received Signal Strength Indicator (RSSI) of BLE use a star-topology on WBANs. The RSSI is a native by-product of any BLE communication and can be obtained without additional hardware or energy-intensive signal processing. By demonstrating that RSSI alone can reliably discriminate among occupationally relevant motions (standing, sitting, and walking) we aim to (i) provide a low-cost, low-power HAR solution, and (ii) facilitate the seamless integration of activity monitoring into existing BLE-based infrastructures (e.g., wearables, asset-tracking systems).

To assess the viability of this approach we conducted a comprehensive measurement campaign involving a heterogeneous cohort of participants. Each subject wore four BLE transceivers at strategically chosen body locations (e.g., chest-to-wrist, waist-to-ankle) together with a body node coordinator (BNC). While performing a predefined set of postures and activities, the RSSI time-series of all on-body links were recorded at the radios' native sampling rates, yielding a dataset

that captures variability due to differing body morphologies, clothing, and movement dynamics. From the raw streams we extracted a rich set of statistical (mean, variance, skewness, kurtosis, inter-quartile range) and spectral (FFT mean and standard deviation, dominant frequency, spectral energy) descriptors within 10 s windows. These features served as inputs to six well-established supervised classifiers: Random Forests (RF), Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Tree (DT), Logistic Regression (LR), Gradient Boosting (GB).

The this paper is organized as follows: Section II describes the measurement setup and protocol; Section III details the experimental for optimization number of sensors used in the HAR classification algorithm; Section IV reports the results; and Section V concludes the paper and outlines future directions.

II. MEASUREMENTS

This section describe in detail how the experimental data were collected and prepared for analysis. It begins with a description of the participant and the hardware setup (BLE transceivers, on-body placement, transmit power, sampling rate). The measurement environment is then characterized, noting the layout, and the on-body link topology. The experimental protocol follows, detailing the postures/activities, trial duration, and number of repetitions, as well as the acquisition pipeline.

A. Participants

The experiment consists of performing activities with sensors placed on the body, where a central device receives the data during each execution. Therefore, a total of nine volunteers with different physical characteristics were selected to participate in the experiment. Details of the group are described in Table I.

TABLE I: Volunteers Profile

Number	Age	Height (m)	Weight (Kg)
1	25	1.80	69
2	23	1.69	72
3	37	1.83	92
4	40	1.82	97
5	35	1.64	80
6	34	1.75	88
7	22	1.82	85
8	41	1.73	92
9	23	1.73	80

B. Experimental Setup

The device used in the experiment is the Nordic Thingy:53 development kit [8], which features two 2.4 GHz antennas and two Arm Cortex-M33 processors. The Thingy:53 is a multi-protocol device with Bluetooth Low Energy 5.2 support. The antenna was positioned close to the skin and fixed on the wrists and in the ankle region.

The transmit power was set to 0 dBm and the measurement interval was 2 minutes for each activity, with data acquisition performed according to the Bluetooth scanning protocol. During data collection, the scan parameters were configured with a scan interval of 100 ms, which defines how often the device initiates a scan cycle, and a scan window of 50 ms, witch specifies the duration of each scanning period within that interval, while the sensors transmit data in advertisement mode, with intervals rangin from 30 ms to 150 ms. In BLE, this interval defines how frequently advertising packets are broadcast by the device.

The star topology was selected for this experiment, with a chest-wrist-ankle node configuration. The other nodes transmitted BLE packets to the central node using the three advertising channels (37, 38 and 39) [9]. Regarding the environment, the experiment was conducted in a closed room with ample free space, where each participant performed the activities while wearing the sensors on their body and maintaining distance from other electronic devices or metallic structures, except for the data collection device.



Fig. 1: Thingy53.

C. Protocol and Activities

The sensors were positioned with their antennas close to the body, with two devices placed on the wrists (sensor 0 on the left side, while sensor 1 on the right side) and two on the ankles (sensor 2 on the left side, while sensor 3 on the right side.), and a similar device was positioned on the thorax of the individual (body central node). The activities performed were: sitting, standing and walking. For activities 1 and 2, the participant was positioned at the center of the room, whereas in activity 3 the actions were performed using the entire available space. Each activity was performed three times per activity, with the same duration defined previously. The interval between each sample was approximately one minute. The setup is illustrated in Fig. 2.

Regarding data storage, the serial interface of the Thingy:53 was used, connected via USB to an Android smartphone. The software employed was Serial USB Terminal, which enables log reading, data storage in .txt format, and real-time visualization with experiments.

D. Data Acquisition and Storage

As previously described, the central device received BLE packets from all sensors (including their RSSI values) and records the results of the current activity in log format. After



Fig. 2: Human activity (standing, sitting and walking).

three rounds, the data are stored in a folder identified by the volunteer ID. The data stream consists of the following variables: timestamping, sensor identifier, and RSSI value. The timestamp is generated by the Android tool during log reception, while the remaining values are obtained directly from the sensors.

III. METHODOLOGY

This section presents the methodology used for HAR based on RSSI data from BLE sensors. The approach encompasses data collection, preprocessing, feature engineering, machine learning model optimization, and sensor combination analysis to identify the optimal configuration for activity classification.

A. Dataset

Data was captured from multiple volunteers performing three distinct activities: walking, standing, and sitting. Each participant executed three measurements of each activity, resulting in a comprehensive dataset that captures the variability in human movement patterns. The raw data consists of timestamped RSSI measurements stored in text files, ensuring accurate temporal alignment of the signal strength readings.

The raw RSSI data underwent a comprehensive preprocessing pipeline to extract meaningful features for classification. Initially, the data was segmented into 10-second windows to capture temporal patterns of human activities. For each sensor within each window, features were extracted from both time and frequency domains to create a rich feature representation.

Time domain features included statistical measures such as mean, median, standard deviation, minimum, and maximum values, along with quartiles (25th and 75th percentiles), kurtosis, and skewness. These features capture the central tendency, dispersion, and shape characteristics of the RSSI signal distribution. Frequency domain features were derived through Fast Fourier Transform (FFT) analysis, including FFT mean and standard deviation, dominant frequency, and spectral energy, which provide insights into the periodic components and frequency content of the signals.

The dataset consisted 972 samples (120 s of data collected for 3 activities with 3 replicates and 9 volunteers for a total of 9720 s, sample is composed of 10 s) with 56 features (14 features per sensor).

B. Machine Learning (ML) applied

To classification were used a different machine learning algorithms were employed for HAR to ensure comprehensive

evaluation and identification of the most suitable approach, beside, each algorithm was optimized using grid search with stratified cross-validation to determine the best hyperparameter configuration:

- **Random Forest** [10]: An ensemble method that constructs multiple decision trees during training and outputs the mode of the classes for classification.
 - Parameters optimized included `n_estimators` with values of 25, 100, and 300; `max_depth` of 5, 15, 30, and None; `min_samples_split` of 2, 10, and 20; `min_samples_leaf` of 1, 4, and 6; and `max_features` of 'sqrt', 'log2', and None.
- **Support Vector Machine** [11]: A supervised learning model that finds an optimal hyperplane in feature space to separate different classes.
 - Optimization considered C values of 0.01, 1, and 100; kernels of 'rbf' and 'poly'; and gamma values of 'scale', 0.01, and 1.
- **K-Nearest Neighbors** [12]: A non-parametric method that classifies data points based on the majority class among their k nearest neighbors.
 - Grid search evaluated `n_neighbors` of 3, 7, and 15; weights of 'uniform' and 'distance'; and metrics of 'euclidean' and 'minkowski'.
- **Decision Tree** [13]: A tree-based model that makes decisions by splitting data based on feature values.
 - Optimization explored `max_depth` values of 3, 10, 20, 30, and None; `min_samples_split` of 2, 10, and 20; criterion of 'gini' and 'entropy'; and `min_samples_leaf` of 1, 4, and 6.
- **Logistic Regression** [14]: A statistical model that uses a logistic function to model a binary dependent variable extended to multiclass classification.
 - Optimization considered C values of 0.01, 1, and 100; penalties of 'l1' and 'l2'; solvers of 'liblinear' and 'lbfgs'; and `max_iter` values of 1000 and 5000.
- **Gradient Boosting** [15]: An ensemble technique that builds models sequentially with each new model correcting errors made by the previous ones.
 - Optimization considered `n_estimators` of 25, 100, and 300; `learning_rate` values of 0.001, 0.1, and 0.3; `max_depth` of 3, 7, 15, and 25; and subsample values of 0.8 and 1.0.

A stratified k-fold cross-validation with 5 folds was employed during hyperparameter optimization to provide robust performance estimates while maintaining the percentage of samples for each target class in each fold. The dataset was divided into training (80%) and testing (20%) sets with stratification to maintain class proportion, ensuring that both sets were representative of the overall class distribution.

C. Simulation: Sensor Combination Analysis

To determine the optimal number of sensors for activity recognition, a systematic evaluation of all possible sensor combinations was conducted, ranging from single sensor configurations to using all four sensors. This analysis aimed to

identify the best trade-off between system complexity and classification performance. For each combination, only features corresponding to the selected sensors were used, ensuring that the evaluation was fair and representative of practical deployment scenarios.

All six ML models were trained and optimized for each sensor combination using the hyperparameter optimization process described previously. Each model was then evaluated on the test set, and the best-performing model for each sensor combination was selected based on classification accuracy. To ensure robust and reproducible results, this entire procedure was repeated using thirty different random seeds for the train-test data split.

IV. RESULTS AND DISCUSSION

This section presents the experimental results obtained from the HAR classification using RSSI data from BLE sensors. We first analyze the performance of different ML techniques, followed by an in-depth examination of sensor combination effectiveness for HAR classification.

A. Machine Learning Technique Performance

To identify the most effective machine learning approach for RSSI-based HAR classification, we evaluated six different algorithms across all sensor combinations and 30 random seeds.

To understand these results, it's important to define the key evaluation metrics used in our analysis. The Accuracy represents the ratio of correctly predicted observations to the total observations, providing an intuitive measure of overall classification performance [16]. The metric F1-Score is the harmonic mean of precision and recall, offering a balanced measure that accounts for both false positives and false negatives, which is particularly valuable in multi-class classification scenarios where class distributions may be imbalanced [16].

Table II presents the average performance of each machine learning algorithm across all sensor combinations and seeds. Gradient Boosting emerged as the top-performing algorithm with an average accuracy of 89.24% (± 4.53), followed closely by Random Forest with 88.72% (± 4.82) and SVM with 87.11% (± 5.03).

TABLE II: Average Model Performance Across All Combinations and Seeds

Algorithm	Accuracy	F1-Score	Training Time (s)
GB	89.24% (± 4.53)	89.20% (± 4.56)	66.77 (± 14.05)
RF	88.72% (± 4.82)	88.67% (± 4.86)	27.40 (± 6.44)
SVM	87.11% (± 5.03)	87.04% (± 5.07)	7.83 (± 12.04)
KNN	85.15% (± 4.86)	84.88% (± 4.99)	0.06 (± 0.03)
DT	81.68% (± 4.69)	81.61% (± 4.74)	0.20 (± 0.06)
LR	78.81% (± 6.35)	78.50% (± 6.60)	2.79 (± 1.51)

The analysis reveals that ensemble methods, particularly Gradient Boosting and Random Forest, consistently outperform the other classifiers, because they can capture complex interactions among the heterogeneous RSSI-based features. Although the results exhibit relatively high standard deviations

across different random seeds reflecting some sensitivity to data splits.

Gradient Boosting yields the highest accuracy but incurs the longest training time (67 s), whereas Random Forest offers a more favorable trade-off, achieving about 89% accuracy with a training time of only 27 s. Traditional classifiers also perform reasonably: SVM reaches 87% accuracy, confirming that kernel-based approaches can handle RSSI features, while K-Nearest Neighbours and Decision Trees deliver moderate results and Logistic Regression attains the lowest performance among the tested models. Fig. 3 illustrates these accuracy distributions, highlighting the stability of the ensemble methods compared with the broader variability of the simpler algorithms.

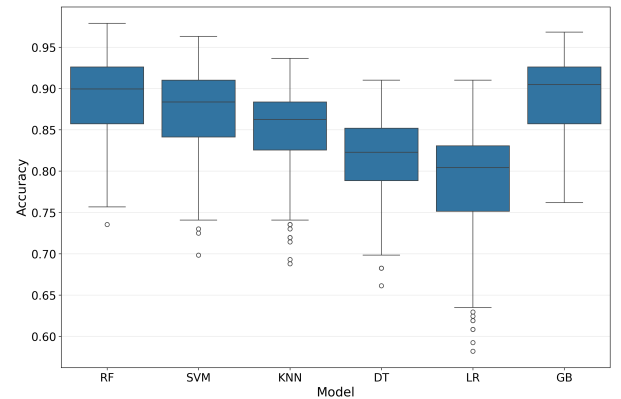


Fig. 3: Accuracy Distribution by ML Algorithm.

B. Sensor Combination Analysis

To determine the optimal number of sensors for HAR classification, we analyzed all possible combinations of 1 to 4 BLE sensors. Table III presents the best sensor combinations for each sensor count, along with their average accuracy and standard deviation. The results demonstrate that increasing the number of sensors generally improves classification performance, with the combination of all four sensors (0-1-2-3) achieving the highest accuracy of 93.77% (± 1.46).

TABLE III: Best Sensor Combinations by Number of Sensors

N. Sensors	Best Combination	Accuracy	Std Dev	Features
1	1	84.90%	± 2.08	14
2	1-3	92.24%	± 1.82	28
3	1-2-3	93.67%	± 1.92	42
4	0-1-2-3	93.77%	± 1.46	56

The analysis highlights a clear trade-off between system complexity and classification performance. A single, well-placed sensor (sensor 1) yields an average accuracy of 83.65 % (84.90 % for the best alone sensor), demonstrating that even minimal hardware can provide useful activity-recognition capability in highly constrained settings. Adding a second sensor dramatically improves results: the 1-3 pair reaches 92.24 % accuracy, and the mean accuracy across all two-sensor combos rises to 91.06 %, confirming that a modest hardware setup can already achieve high performance. Incorporating a third sensor (1-2-3) pushes accuracy

to 93.67 % (average 93.15 % for three-sensor sets), offering a substantial gain over two sensors while keeping system complexity manageable. Using all four sensors (0-1-2-3) yields the highest score of 93.77 % (± 1.46), but the marginal improvement over the three-sensor arrangement indicates that sensor 0 contributes little additional information. Consequently, a two-sensor configuration provides an excellent balance of cost and accuracy, whereas three sensors are advisable when the highest possible performance is required.

Figure 4 shows the distribution of accuracy values for each sensor count, demonstrating the improvement in performance as more sensors are added and the diminishing returns when moving from three to four sensors.

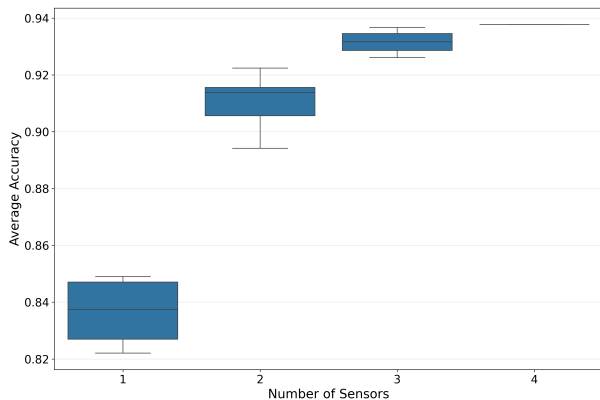


Fig. 4: Accuracy Distribution by Number of Sensors.

The Fig. 5 shows the top 10 sensor combinations by accuracy, further supporting the finding that combinations including sensors 1, 2, and 3 consistently perform well.

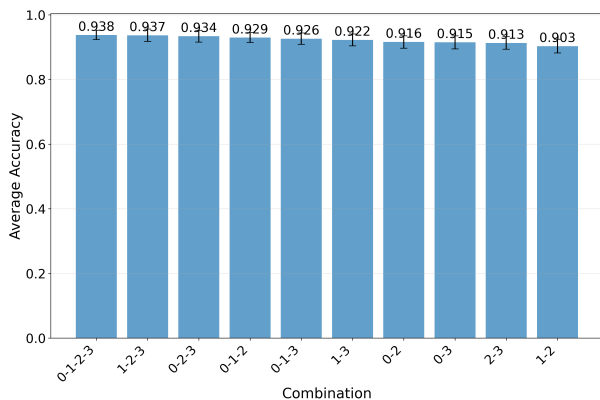


Fig. 5: Top 10 Sensor Combinations by Accuracy.

V. CONCLUSIONS AND FUTURE WORK

This study confirms that HAR can be performed reliably using only the RSSI from BLE sensors in WBANs, alternative or eliminating the need for dedicated wearables or specialized hardware. An optimal four-sensor layout achieved a classification accuracy of 93.77 %, while a minimal two-sensor configuration (sensors 1-3) still delivered an impressive 92.24 % accuracy (sufficient for most real-world applications).

The high performance stems from distinct RSSI-based propagation patterns generated by human motion, effective time- and frequency-domain feature extraction, and use machine-learning models (gradient-boosting ensembles with tuned hyper-parameters). The sensor-selection analysis highlights that most of the discriminative information is captured by just two strategically placed modules, offering a strong trade-off between accuracy, cost, and system complexity.

Future work will extend the approach to a broader set of activities and environments, explore sensor-fusion with other modalities, and implement real-time processing on embedded platforms to facilitate practical, large-scale deployments.

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