RSSI-Based Passenger Movement Classification for Non-Intrusive Public Transport Monitoring

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***Abstract*—Accurate monitoring of passenger flows in public transport is essential for service optimization and network planning, yet traditional counting methods face limitations in coverage, cost, and privacy preservation. This paper presents a novel approach for classifying passenger movements using temporal sequences of Wi-Fi Received Signal Strength Indicator (RSSI) measurements. We introduce a dataset collected in a controlled experimental environment that simulates public transport scenarios, capturing the distinctive signal patterns associated with four fundamental movement classes: boarding the vehicle, alighting from the vehicle, remaining inside, and remaining at the bus stop. By analyzing the temporal evolution of RSSI values over ten-second observation windows, our approach enables non-intrusive distinction between static and transitional states without requiring specialized hardware or compromising passenger anonymity. Experimental evaluation using multiple machine learning classifiers demonstrates the feasibility of RSSI-based movement classification, providing a cost-effective complement to existing automatic passenger counting systems for intelligent transportation applications.**

***Index Terms*—Passenger counting, RSSI fingerprinting, Wi-Fi sensing, public transport, machine learning, intelligent transportation systems, urban mobility**

I. Introduction

Accurate passenger flow data is essential for service optimization and network planning, yet traditional counting approaches—manual surveys, ticketing systems, infrared sensors, and Automatic Passenger Counting (APC) devices—suffer from high costs, incomplete coverage, and privacy concerns [1]. The ubiquity of Wi-Fi-enabled devices offers new avenues for non-intrusive sensing: Received Signal Strength Indicator (RSSI) signatures enable movement pattern recognition while preserving anonymity, using only standard networking equipment [2]–[4].

This paper proposes a passenger boarding and alighting classification framework based on temporal RSSI sequences. By tracking signal evolution over ten-second observation windows, the methodology distinguishes four movement patterns: remaining inside the vehicle, remaining at the stop, boarding, and alighting. Without requiring precise localization or specialized hardware. The principal contributions are:

1) An RSSI-based movement classification framework exploiting temporal signal evolution;
2) An experimental dataset comprising approximately 1,360 labelled samples across four classes, collected from four smartphone models spanning three brands;
3) A comprehensive evaluation of 38 machine learning classifiers with Bayesian hyperparameter optimization;
4) Feature importance analysis revealing the discriminative role of initial and mid-trajectory RSSI measurements;
5) A privacy-preserving sensing approach that operates without device identification.

The remainder of this paper reviews related work (section II), describes the experimental setup (section III), presents exploratory data analysis (section IV), presents results (section V), and concludes with future directions (section VI).

II. Related Work

A. Automatic Passenger Counting

Conventional APC systems rely on infrared sensors, pressure mats, or video-based detection [5], yet claimed accuracies of 98% frequently drop to 53–74% under real-world conditions [1]. Vision-based approaches can reach 94% accuracy [6] but remain hampered by occlusion, lighting variability, and privacy concerns. Recent edge AI camera systems [7] reduce computational cost but still require per-vehicle hardware installation.

B. Wi-Fi-Based Sensing and Research Gap

Wi-Fi-based passenger counting has been demonstrated through probe request analysis [8], with systems such as iABACUS achieving up to 100% detection in static settings [2]. While Channel State Information (CSI)-based systems yield richer information with over 94% accuracy [9], [10], they require specialized hardware. RSSI-based methods remain practical with off-the-shelf equipment; Simončič et al. [3] attained over 96% accuracy for presence monitoring despite Media Access Control (MAC) randomization challenges. Oransirikul et al. [11] demonstrated that Wi-Fi activity patterns can distinguish passengers from non-passengers, though their approach relies on traffic volume rather than temporal signal evolution.

Despite this progress, machine learning classification of movement patterns from RSSI time series has received comparatively little attention. Existing work treats RSSI primarily as static fingerprints for indoor localization [4] rather than as temporal sequences encoding movement dynamics. Our work addresses this gap by casting passenger movement detection as a supervised classification problem over temporal RSSI evolution, enabling real-time trajectory classification with a single access point at the vehicle door.

III. Experimental Setup

This section outlines the physical data collection environment and the machine learning experimental framework devised for passenger movement classification.

A. Physical Data Collection Setup

Controlled experiments were carried out in an indoor environment that emulates public transport interactions, allowing reproducible data collection under both isolated and noisy conditions.

1) Environmental Configuration: The environment was divided into two zones (Figure 1). Zone A (Vehicle Interior) consisted of a closed room simulating a bus interior, with a Wi-Fi access point positioned adjacent to the doorway. Zone B (Bus Stop) was the corridor outside, representing the boarding area. The wall and door between zones introduce signal attenuation, generating distinctive RSSI patterns during transitions.

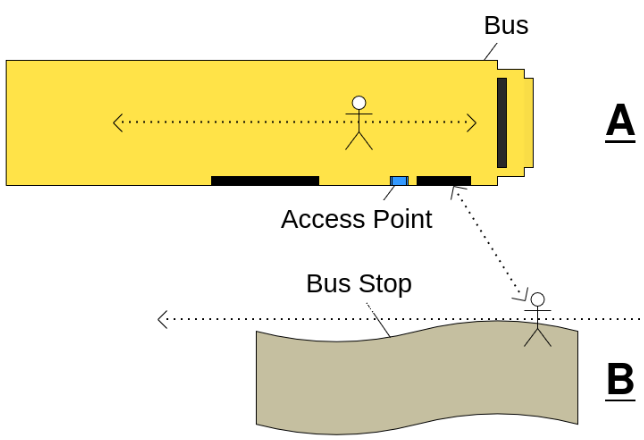

Figure 1. Experimental environment simulating a public transport scenario.

2) Data Acquisition: Data was collected using a Python script interfacing with the Access Point via Ethernet. Each trial comprised a **10-second window** with **10 RSSI samples at 1 Hz**. Devices maintained periodic low-overhead traffic (ICMP) to ensure consistent RSSI reporting. Four smartphones from three brands were employed to introduce hardware and chipset variability: Samsung Galaxy S20 (Android 13), Samsung Galaxy S23 (Android 14), POCO X7 Pro (Android 14), and Xiaomi Redmi 4 (Android 6). This selection spans a wide range of Wi-Fi chipset generations and transmit power characteristics, improving the generalizability of trained models.

Four movement classes were defined: **A→A** (remaining inside), **B→B** (remaining at stop), **A→B** (alighting), and **B→A** (boarding). Collection occurred under two scenarios: *Isolated* (single device, 20 repetitions per class per device) and *Noisy* (four devices simultaneously performing paired movements).

3) Preprocessing and Dataset Structure: Raw data underwent the following preprocessing steps: (1) *Temporal Aggregation*, where 10 RSSI measurements per trial were aggregated into a feature vector $\mathbf{R} = [r_1, \ldots, r_{10}]$; (2) *Device Isolation* using MAC addresses; (3) *Labeling* with movement class and noise indicator; and (4) *Feature Filtering* to retain only RSSI values.

Device isolation relies on MAC addresses reported by the access point for associated clients. Although modern mobile operating systems randomize MAC addresses during probe requests, this randomization does not affect our methodology: once a device establishes a Wi-Fi association, it retains a consistent MAC address for the duration of the session. Since each 10-second observation window operates well within a single association period, device identification remains stable throughout the measurement interval.

Prior to model training, *Feature Scaling* was applied using standardization (z-score normalization), which transforms each feature to zero mean and unit variance. This step is essential for classifiers sensitive to feature magnitudes, such as Support Vector Machines (SVMs), Gaussian Process (GP) classifiers, Multi-Layer Perceptrons (MLPs), and logistic regression, as these distance-based and gradient-based methods may otherwise suffer from degraded convergence speed and classification performance when operating on raw RSSI value ranges.

The resulting dataset contains 1,356 samples, each representing a 10-second trajectory with a corresponding movement class label, enabling analysis of both absolute signal strength and temporal evolution.

4) Experimental Scenarios: To comprehensively evaluate the impact of data collection conditions on classification performance, three distinct experimental scenarios were defined:

Combined Dataset: The complete dataset containing all 1,356 samples from both isolated and noisy collection conditions. This scenario represents the most realistic deployment setting, where the classifier must generalize across varying environmental conditions.

Isolated-Only Dataset: A subset containing exclusively samples collected under isolated conditions (single device, $n = 160$). This scenario provides an upper-bound estimate of classification performance under ideal conditions with minimal signal interference.

Noisy-Only Dataset: A subset containing exclusively samples collected with simultaneous multi-device activity ($n = 1,196$). This scenario evaluates classifier robustness under challenging conditions that closely approximate real-world public transport environments.

Comparing across these scenarios allows for a quantitative assessment of how environmental noise affects classification accuracy and sheds light on the operational boundaries of RSSI-based movement detection.

B. Machine Learning Experimental Framework

The following subsection details the classifier selection rationale, evaluation methodology, and performance metrics adopted in our experimental protocol.

1) Classifier Selection: A total of 38 classification algorithms spanning multiple paradigms were evaluated to ensure thorough benchmarking. The classifier families were chosen based on their established effectiveness in RSSI-based classification tasks [12], [13]:

Support Vector Machines (SVM): SVMs with Radial Basis Function (RBF) and linear kernels were included due to their demonstrated superiority in Wi-Fi fingerprinting tasks. Prior studies on indoor localization using RSSI have shown SVMs achieving accuracies exceeding 90% for location classification [4], [14]. The RBF kernel effectively captures non-linear relationships in signal strength patterns.

Ensemble Methods: Random Forest and Extra Trees were selected for their robustness to noise and ability to model complex decision boundaries without extensive hyperparameter tuning [12]. Gradient boosting variants (XGBoost, LightGBM, CatBoost) were included based on their state-of-the-art performance in tabular classification tasks, with CatBoost demonstrating particular effectiveness for categorical features [15].

Gaussian Process Classifier: GPs provide probabilistic predictions with uncertainty quantification, particularly valuable for RSSI data where signal variability is inherent. The RBF kernel enables automatic adaptation to the intrinsic dimensionality of temporal RSSI sequences.

Neural Networks: MLPs with varying architectures (small, medium, large) were evaluated to assess whether deeper representations improve classification over traditional methods for this feature space dimensionality.

Stacking and Voting Ensembles: Meta-learning approaches combining heterogeneous base learners were included to leverage complementary classifier strengths, a strategy shown to improve robustness in transportation sensing applications [6].

2) Data Partitioning Strategy: The dataset was partitioned using **stratified sampling** with an 80%/20% train-test split. Stratified sampling ensures that class distributions are preserved in both partitions, which is critical for multi-class classification problems where class imbalance could otherwise bias model evaluation. This approach maintains the original proportion of each movement class (AA, BB, AB, BA) in both training and testing sets.

3) Cross-Validation Protocol: Model training employed **5-fold stratified cross-validation**, a methodology widely recommended for robust classifier evaluation. Stratified K-fold cross-validation maintains class ratios across all folds, ensuring that minority classes receive adequate representation during training and validation. This technique reduces variance in performance estimates compared to simple hold-out validation.

To assess result stability, experiments were repeated with three random seeds (3, 5, and 42), and metrics were aggregated across runs. This multi-seed evaluation quantifies classifier sensitivity to random initialization and data shuffling.

4) Hyperparameter Optimization: To ensure fair comparison and optimal performance across classifier families, systematic hyperparameter optimization was conducted using Optuna [16], a state-of-the-art Bayesian optimization framework. Optuna employs the Tree-structured Parzen Estimator (TPE) algorithm to efficiently explore high-dimensional hyperparameter spaces, focusing search efforts on promising regions.

For each tunable classifier, extensive hyperparameter searches were performed with budgets ranging from 50 to over 1,300 trials depending on model complexity. The optimization objective was accuracy during 5-fold stratified cross-validation on the training set. This approach yields classifier configurations specifically adapted to the RSSI feature space characteristics.

The hyperparameter search spaces were defined based on recommended ranges from the literature and practical considerations. Ensemble methods (Random Forest, Extra Trees, Gradient Boosting variants) were tuned over tree depth, number of estimators, and regularization parameters. SVMs were optimized for the regularization parameter C and kernel coefficients. Neural network configurations explored layer architectures, learning rates, and regularization strengths.

The complete hyperparameter search spaces and the optimal configurations identified for each classifier are provided as supplementary material and are available on GitHub [17].

5) Performance Metrics: Four complementary metrics were employed to provide a comprehensive performance characterization:

Accuracy: The proportion of correctly classified samples. While intuitive, accuracy can be misleading for imbalanced datasets.

Weighted F1-Score: The harmonic mean of precision and recall, weighted by class support. This metric balances false positives and false negatives while accounting for class distribution.

Balanced Accuracy: The arithmetic mean of per-class recall values, ensuring equal contribution from each class regardless of prevalence.

Matthews Correlation Coefficient (MCC): Selected as the primary evaluation criterion, as this metric offers a reliable and balanced evaluation of classification models, particularly in scenarios involving imbalanced datasets or when assessing performance across multiple classes [18], [19]. Matthews Correlation Coefficient (MCC) ranges from -1 to $+1$, producing high scores only when all confusion matrix categories achieve strong results.

IV. Exploratory Data Analysis

Ahead of classifier training, an exploratory data analysis was carried out to gauge the discriminative potential of temporal RSSI signatures and to characterize signal behaviour across different passenger movement classes.

A. Dataset Composition

The final dataset is roughly balanced, comprising around 340 samples per movement class. For each class, 40 samples were gathered under isolated conditions, while the remaining samples were obtained during simultaneous device activity, thereby introducing controlled signal interference. This balance ensures that the exploratory analysis and subsequent results reflect both ideal and realistic operating conditions.

B. Temporal RSSI Characteristics

The temporal evolution of RSSI values serves as the primary discriminative feature between movement classes. Figure 2 depicts the mean RSSI trajectory over the 10-second observation window for each class.

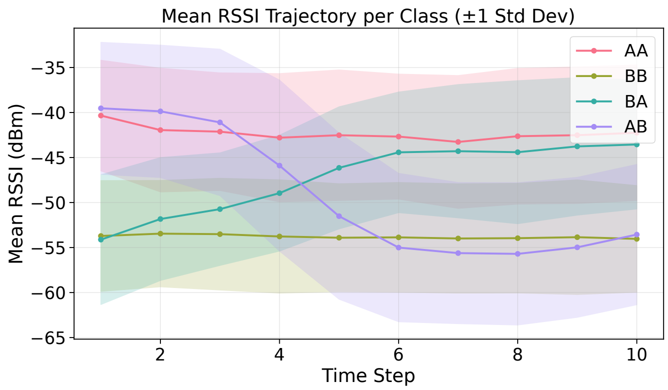

Figure 2. Temporal evolution of RSSI values over the 10-second observation window for each movement class plus the standard deviation.

Static states (**AA and BB**) exhibit relatively stable signal levels over time, albeit with distinct average magnitudes due to their spatial separation from the access point. In contrast, transitional movements display clear monotonic trends. The boarding class ($\mathbf{B} \rightarrow \mathbf{A}$) shows a consistent increase in RSSI as the devices move toward the access point, while the alighting class ($\mathbf{A} \rightarrow \mathbf{B}$) presents a pronounced decrease as physical obstructions attenuate the signal.

These contrasting temporal patterns offer a compelling rationale for leveraging RSSI sequences in movement classification.

Although the standard deviation bands exhibit considerable overlap across classes, indicating substantial signal variability inherent to wireless environments, machine learning classifiers can effectively mitigate this noise by learning the underlying temporal trends rather than relying on instantaneous measurements. By capturing the discriminative patterns in RSSI evolution over the observation window, these models can filter out stochastic fluctuations and focus on the systematic differences between movement classes, thereby enabling robust classification despite challenging radio conditions.

V. Results and Discussion

This section presents the experimental results from evaluating 38 machine learning classifiers on the RSSI-based passenger movement dataset and analyses their implications across three experimental scenarios.

A. Comparative Analysis Across Scenarios

Table I presents the performance comparison of top classifiers across the three experimental scenarios, revealing the substantial impact of data collection conditions on classification performance.

Table I
Performance Comparison Across Experimental Scenarios (MCC)

Classifier	Combined	Isolated-Only	Noisy-Only
KNN (k=5)	0.692 ± 0.029	$\mathbf{0.907 \pm 0.061}$	0.704 ± 0.025
KNN (k=3)	0.690 ± 0.046	0.882 ± 0.068	0.702 ± 0.043
LinearSVC	0.726 ± 0.039	0.867 ± 0.060	0.716 ± 0.031
LogisticRegression (L2)	0.743 ± 0.044	0.866 ± 0.028	0.731 ± 0.009
SVC (Linear)	0.750 ± 0.023	0.850 ± 0.088	0.731 ± 0.037
StackingEnsemble	0.749 ± 0.020	0.851 ± 0.122	0.768 ± 0.023
ExtraTrees	0.737 ± 0.013	0.836 ± 0.041	0.755 ± 0.021
GaussianProcess	$\mathbf{0.756 \pm 0.033}$	0.414 ± 0.052	0.755 ± 0.028
SVC (RBF)	0.755 ± 0.021	0.825 ± 0.101	0.754 ± 0.016
CatBoost	0.746 ± 0.017	0.782 ± 0.063	$\mathbf{0.770 \pm 0.013}$

The isolated-only scenario yielded markedly superior performance, with K-Nearest Neighbors (KNN) (k=5) reaching an MCC of 0.907—a 31% relative improvement over the combined dataset. This increase stems from the absence of inter-device signal interference, producing cleaner RSSI patterns with more distinct class separations. Simpler classifiers such as KNN, which rely on local neighbourhood structure, benefit disproportionately from this increased separability.

Conversely, the GP classifier suffered notable degradation in the isolated scenario (MCC: 0.414) despite attaining the highest MCC (0.756) on the combined dataset. This paradox is explained by the limited sample size ($n = 160$), which proves insufficient for reliable kernel hyperparameter estimation. On the combined dataset, the GP's probabilistic framework and RBF kernel flexibility enable effective modelling of non-linear decision boundaries without extensive manual tuning.

The noisy-only scenario, representing the most realistic operational conditions, showed performance on par with the combined dataset, with CatBoost attaining the highest MCC (0.770). This consistency indicates that the combined dataset's performance is largely driven by the noisy samples, which constitute 88% of the total data. Gradient boosting methods demonstrated particular robustness to signal interference.

B. Per-Class and Error Analysis

Table II presents the per-class metrics for the best classifier in each scenario, averaged across three random seeds.

In the isolated scenario, all four classes exceed an F1-score of 0.86, with BB reaching 0.963 at perfect recall (1.000). The absence of inter-device interference produces cleaner RSSI patterns, resulting in per-class F1-scores 10–15% higher than in the combined and noisy scenarios.

Across all three scenarios, BB (bus stop) is the most accurately classified class, due to the consistent low RSSI values caused by the physical barrier separating Zone B from the access point. AB (alighting) maintains high recall (0.882–0.958) but comparatively lower precision, as the declining RSSI pattern during exit partially overlaps with the static low-RSSI signature of BB.

AA (inside vehicle) presents the lowest recall in the combined scenario (0.726), primarily from misclassification as BA. Both classes occupy Zone A near the access point, producing similar high-RSSI magnitudes. Although their temporal

Table II
PER-CLASS PERFORMANCE METRICS ACROSS SCENARIOS (MEAN OVER THREE SEEDS)

Scenario	Class	Precision	Recall	F1-Score	MCC
Combined (GP)	AA (Inside)	0.784	0.726	0.754	0.676
	BB (Stop)	0.871	0.892	0.882	0.841
	BA (Boarding)	0.834	0.765	0.798	0.736
	AB (Alighting)	0.779	0.882	0.827	0.768
	Weighted Avg	**0.817**	**0.816**	**0.815**	**0.756**
Isolated KNN ($k=5$)	AA (Inside)	0.896	0.875	0.866	0.842
	BB (Stop)	0.933	1.000	0.963	0.952
	BA (Boarding)	0.963	0.875	0.910	0.891
	AB (Alighting)	0.958	0.958	0.958	0.944
	Weighted Avg	**0.938**	**0.927**	**0.924**	**0.907**
Noisy (CatBoost)	AA (Inside)	0.784	0.800	0.791	0.721
	BB (Stop)	0.891	0.844	0.866	0.824
	BA (Boarding)	0.877	0.778	0.822	0.772
	AB (Alighting)	0.778	0.883	0.826	0.767
	Weighted Avg	**0.833**	**0.826**	**0.826**	**0.770**

dynamics differ—stable values for AA versus an increasing trend for BA—this distinction is subtle within the 10-second observation window. This confusion is reduced in the isolated scenario (AA recall: 0.875), where the absence of interference makes temporal patterns more separable.

BA (boarding) exhibits the most scenario-dependent recall, ranging from 0.765 (combined) to 0.875 (isolated). In multi-device conditions, co-channel interference partially obscures the characteristic increasing RSSI profile associated with an approaching passenger.

C. Confusion Matrix Analysis

Figure 3 presents the normalized confusion matrix for the GP classifier.

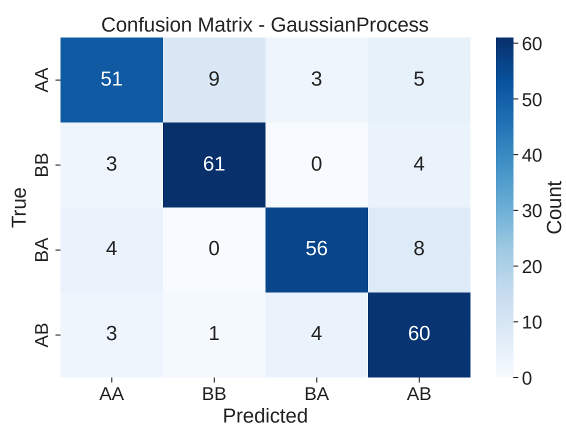

Figure 3. Confusion matrix for the GP classifier, demonstrating strong diagonal dominance with minimal inter-class confusion.

The confusion matrix confirms that classification errors concentrate between spatially adjacent classes. The AA–BA confusion reflects RSSI magnitude similarity when devices are near the access point, while the AB–BB confusion arises from both classes sharing lower RSSI values characteristic of the exterior zone. These patterns suggest that additional features or longer observation windows could improve discrimination between static and transitional states.

D. Model Stability

Figure 4 illustrates the MCC variability for top classifiers across the three random seeds.

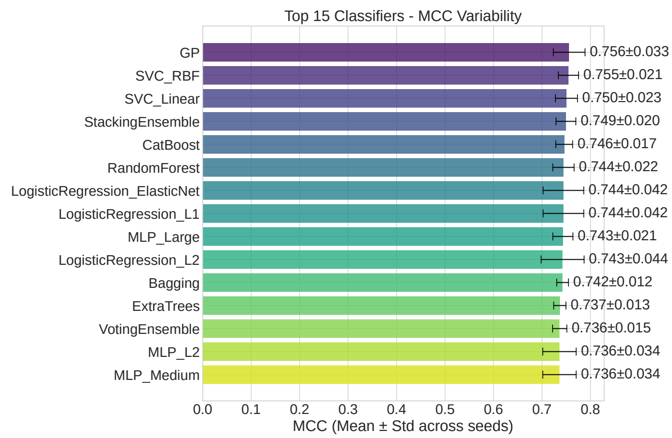

Figure 4. MCC variability for top classifiers, in combined dataset, demonstrating consistent ranking stability.

Top-performing classifiers maintain consistent relative rankings across seeds. Kernel-based methods (GP, SVC) and ensemble approaches (Stacking, CatBoost) displayed the lowest variability, a desirable property for deployment scenarios where model retraining may occur with different data partitions.

E. Feature Importance

Figure 5 illustrates the mean feature importance across interpretable classifiers.

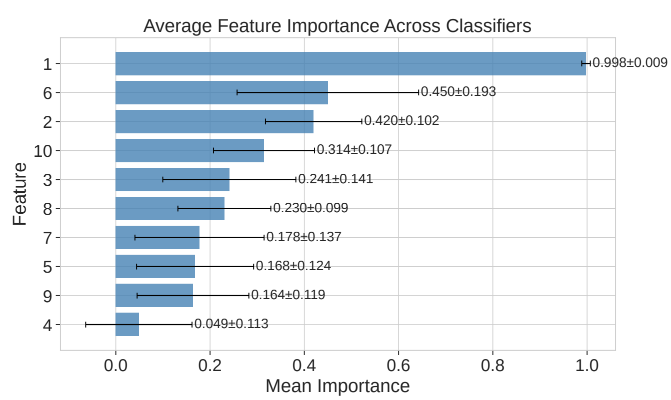

Figure 5. Mean feature importance across classifiers, with standard deviation, to the $[0, 1]$ range using min-max normalization

Initial RSSI measurements (features 1–3) contribute most significantly to classification decisions, capturing the starting position and enabling immediate distinction between static and transitional states. Feature 1 exhibits the highest mean importance (normalized score: 0.99) with universal agreement among classifiers (standard deviation: 0.009). The elevated importance of feature 6 (mid-trajectory) indicates that classifiers also rely on signal evolution to confirm movement direction, validating the use of sequential RSSI measurements over aggregate statistics.

F. Hyperparameter Configuration

While extensive hyperparameter optimization was performed for nine classifier families using Optuna, the GP classifier employed default configurations with an RBF kernel.

Details regarding the hyperparameter search spaces and the optimal configurations for all optimized classifiers are provided as supplementary material on GitHub [17]. The GP configuration is presented in Table III.

Table III
GP HYPERPARAMETERS

Parameter	Value
Kernel	$1.0 \times \text{RBF}(1.0)$
Kernel Length Scale	Optimized during fitting
Optimizer	L-BFGS-B
Max Iterations	100
Multi-class Strategy	One-vs-Rest

The RBF kernel automatically learns optimal length scale parameters during training, adapting to the intrinsic dimensionality of RSSI sequences. Notably, the GP achieved top performance without requiring the extensive hyperparameter search applied to other classifiers, suggesting that its probabilistic formulation is well-suited to the RSSI feature space.

G. Deployment Considerations

The experimental results inform practical classifier selection. For high-interference environments with multiple simultaneous devices, gradient boosting methods (CatBoost, XGBoost) and ensemble approaches offer the best balance of accuracy and robustness. In controlled settings with minimal device density, simpler classifiers such as KNN achieve superior performance with reduced computational overhead. For general deployment across varying conditions, SVC with RBF kernel provides consistent performance with acceptable variance.

The notable performance improvement in isolated conditions (MCC up to 0.907) indicates that signal interference is the chief limiting factor. Deployment strategies that mitigate interference, like dedicated frequency channels or directional antennas, could markedly enhance performance. Nevertheless, the results under noisy conditions (MCC > 0.77) confirm that RSSI-based movement classification remains viable as a complementary passenger counting technology even in challenging environments.

H. Limitations

Several limitations warrant discussion. The controlled experimental environment, while designed to simulate public transport conditions, may not capture all sources of variability present in operational settings, such as passenger density fluctuations, vehicle movement, and diverse access point placements. The 10-second observation window, while suitable for typical boarding and alighting actions, may be insufficient for slower movements; adaptive window lengths could improve accuracy. The limited isolated dataset size ($n = 160$) further constrains reliability estimates for complex classifiers in that scenario.

Regarding energy consumption, the proposed approach imposes minimal overhead on passenger devices, as it leverages existing Wi-Fi associations without requiring additional active scanning. The access point performs passive RSSI sampling, introducing no extra power drain on user devices. However, maintaining continuous Wi-Fi connectivity may affect battery life on devices with aggressive power-saving policies. On the infrastructure side, the access point's processing and energy overhead, while generally modest, may increase with higher device densities and more computationally demanding classification models, necessitating efficient implementation for real-time inference. Furthermore, certain router operating systems may enter power-saving modes that could disrupt continuous RSSI monitoring; careful firmware configuration is therefore required to ensure uninterrupted data collection. A quantitative characterization of energy impact, on both client devices and access point hardware, across different deployment scales remains an avenue for future investigation.

Modern mobile operating systems employ MAC address randomization during Wi-Fi probe requests, which can complicate device tracking in passive sensing scenarios. Our approach mitigates this challenge by relying on established Wi-Fi associations rather than passive scanning: once a device associates with the access point, it maintains a consistent MAC address throughout the session, and the 10-second observation window operates well within a single association period, ensuring stable device identification. Nevertheless, devices that do not actively connect to the access point (or that cycle their MAC address between association events) remain untrackable, imposing a practical ceiling on detection coverage. Variations in device hardware and operating system behaviour may further affect RSSI reporting consistency in practice.

VI. CONCLUSIONS

This paper has presented a new approach for classifying passenger movements in public transport using temporal sequences of Wi-Fi RSSI measurements. The proposed methodology enables non-intrusive distinction between four fundamental movement classes using only standard Wi-Fi access point infrastructure.

The GP classifier attained the highest performance on the combined dataset, with an MCC of 0.756, validated across multiple random seeds. SVMs and regularized logistic regression variants yielded comparable results, confirming that both kernel-based and linear methods can effectively exploit the temporal structure of RSSI sequences.

Per-class analysis revealed that static states at the bus stop and transitional movements are more readily distinguished owing to their characteristic signal patterns, whereas the static state inside the vehicle posed the greatest classification challenge because of its proximity-based similarity with the boarding class.

The results demonstrate that RSSI-based passenger movement classification offers a viable, cost-effective, and privacy-preserving complement to existing APC technologies, requiring no specialized hardware beyond standard Wi-Fi infrastructure.

Future work includes validation in operational public transport environments, integration of complementary sensor modalities, development of adaptive observation windows, and extension of the methodology to estimate complete Origin-Destination (OD) matrices [20] through temporal aggregation of boarding and alighting events.

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References

[1] C. Pronello and X. R. Garzón Ruiz, "Evaluating the performance of video-based automated passenger counting systems in real-world conditions: A comparative study," *Sensors*, vol. 23, no. 18, 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/18/7719

[2] M. Nitti, F. Pinna, L. Pintor, V. Pilloni, and B. Barabino, "iabacus: A wi-fi-based automatic bus passenger counting system," *Energies*, vol. 13, no. 6, 2020. [Online]. Available: https://www.mdpi.com/1996-1073/13/6/1446

[3] A. Simoni, M. Mohori, M. Mohori, and A. Hrovat, "Non-intrusive privacy-preserving approach for presence monitoring based on wifi probe requests," *Sensors*, vol. 23, no. 5, 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/5/2588

[4] C. Agualimpia-Arriaga, S. Govindasamy, B. Soni, C.-I. Páez-Rueda, and A. Fajardo, "Rssi-based indoor localization using machine learning for wireless sensor networks: A recent review," in *2024 IEEE ANDESCON*, 2024, pp. 1–6.

[5] B. Barabino, M. Di Francesco, and S. Mozzoni, "An offline framework for handling automatic passenger counting raw data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 6, pp. 2443–2456, 2014.

[6] C. Wiboonsiriruk, E. Phaisangittisagul, C. Srisurangkul, and I. Kumazawa, "Efficient passenger counting in public transport based on machine learning," in *TENCON 2023 - 2023 IEEE Region 10 Conference (TENCON)*, 2023, pp. 214–219.

[7] K. Ono, T. Uchibayashi, C. Sueyoshi, K. Inenaga, and Y. Yasutake, "Real-time passenger detection and counting using edge ai camera," in *2025 IEEE Cyber Science and Technology Congress (CyberSciTech)*, 2025, pp. 606–609.

[8] T. A. Myrvoll, J. E. Håkegård, T. Matsui, and F. Septier, "Counting public transport passenger using wifi signatures of mobile devices," in *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, 2017, pp. 1–6.

[9] H. Wang and I. W.-H. Ho, "Csi-based passenger counting on public transport vehicles with multiple transceivers," in *2024 IEEE Wireless Communications and Networking Conference (WCNC)*, 2024, pp. 1–6.

[10] J. Guo, W. Zhuang, Y. Mao, and I. Ho, "Rssi-assisted csi-based passenger counting with multiple wi-fi receivers," in *IEEE Wireless Communications and Networking Conference (WCNC)*, 2025.

[11] T. Oransirikul, I. Piumarta, and H. Takada, "Classifying passenger and non-passenger signals in public transportation by analysing mobile device wi-fi activity," *Journal of Information Processing*, vol. 27, pp. 25–32, 2019.

[12] N. Singh, S. Choe, and R. Punmiya, "Machine learning based indoor localization using wi-fi rssi fingerprints: An overview," *IEEE Access*, vol. 9, pp. 127 150–127 174, 2021.

[13] B. Zholamanov, A. Saymbetov, M. Nurgaliyev, A. Bolatbek, G. Dosymbetova, N. Kuttybay, S. Orynbassar, A. Kapparova, N. Koshkarbay, and O. F. Beyca, "Rssi fingerprint-based indoor localization solutions using machine learning algorithms: A comprehensive review," *Smart Cities*, vol. 8, no. 5, 2025. [Online]. Available: https://www.mdpi.com/2624-6511/8/5/153

[14] C. Jain, G. V. S. Sashank, V. N, and S. Markkandan, "Low-cost ble based indoor localization using rssi fingerprinting and machine learning," in *2021 Sixth International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, 2021, pp. 363–367.

[15] L. Fabre, C. Bayart, Y. Kone, O. Manout, and P. Bonnel, "A machine learning approach to estimate public transport ridership using wi-fi data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 26, no. 1, pp. 906–915, 2025.

[16] T. Akiba, S. Sano, T. Yanase, T. Ohta, and M. Koyama, "Optuna: A next-generation hyperparameter optimization framework," in *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, ser. KDD '19. New York, NY, USA: Association for Computing Machinery, 2019, pp. 2623–2631. [Online]. Available: https://doi.org/10.1145/3292500.3330701

[17] A. Ribeiro, G. Matos, and M. Antunes, "Hyperparameter optimization supplementary materials," https://github.com/ATNoG/inMotion/tree/main/docs/supplementary/hyperparameter-optimization, 2026, accessed: 2026-02-10.

[18] D. Chicco and G. Jurman, "The advantages of the matthews correlation coefficient (mcc) over f1 score and accuracy in binary classification evaluation," *BMC Genomics*, vol. 21, no. 1, p. 6, 2020.

[19] ——, "The matthews correlation coefficient (mcc) should replace the roc auc as the standard metric for assessing binary classification," *BioData Mining*, vol. 16, no. 1, p. 4, 2023.

[20] S. Cerqueira, E. Arsénio, and R. Henriques, "Inference of dynamic origin–destination matrices with trip and transfer status from individual smart card data," *European Transport Research Review*, vol. 14, no. 1, p. 42, 2022. [Online]. Available: https://doi.org/10.1186/s12544-022-00562-1