



Real-Time Lecturer Localization via Edge-Standardized Wi-Fi Fingerprinting on Android

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Abstract.

Purpose: This research aims to develop a highly responsive Indoor Positioning System (IPS) to locate lecturers in real-time within educational facilities by mitigating Access Point (AP) Churn through decentralized data preprocessing.

Methods: A Wi-Fi fingerprinting dataset comprising 1,428 observations from 40 Access Points (APs) was collected across lecturer operational areas. Missing RSSI values were standardized to -100 dBm on the Android client before transmission. Random Forest, Decision Tree, Support Vector Machine (SVM), and K-Nearest Neighbor (K-NN) were comparatively evaluated using stratified cross-validation and validated through real-time Android deployment.

Result: The Random Forest algorithm achieved the best performance with 97.90% accuracy and 97.86% F1-score. The proposed Android-based workflow enabled reliable real-time lecturer localization while maintaining consistent RSSI preprocessing between the mobile application and the cloud inference model.

Novelty: The contribution of this study is an Android-based edge preprocessing framework that standardizes missing RSSI values before cloud inference and demonstrates its practicality through comparative machine learning evaluation in a real-time lecturer localization system.

Keywords: Android application, AP churn, Edge computing, Lecturer localization, Machine learning, Wi-Fi fingerprinting

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INTRODUCTION

Locating lecturers within large campus facilities can be challenging, particularly when lecturers move between offices, laboratories, and teaching spaces. To address this issue, Indoor Positioning Systems (IPS) based on existing Wi-Fi infrastructure have emerged as a practical and cost-effective solution because they utilize widely available Wireless Local Area Network (WLAN) deployments without requiring additional dedicated hardware [1], [2], [3], [4]. By exploiting the Received Signal Strength Indicator (RSSI) through Wi-Fi fingerprinting, smartphones can estimate indoor locations with high accuracy while avoiding the deployment cost associated with Bluetooth beacons, Ultra-Wideband (UWB), or other specialized localization technologies [5], [6], [7], [8], [9].

However, implementing Wi-Fi fingerprinting for dynamic human localization remains challenging because RSSI measurements are highly sensitive to environmental changes, signal attenuation, multipath propagation, and user mobility. One of the most critical issues is Access Point (AP) Churn, where mobile devices temporarily fail to detect previously observed Access Points due to movement, physical obstructions, or variations in wireless propagation. Consequently, missing RSSI values frequently occur and may significantly reduce localization accuracy if they are not handled consistently [10], [11], [12], [13], [14], [15], [16], [17], [18].

Previous studies have proposed various approaches to mitigate missing RSSI values through standardization techniques, feature engineering, and machine learning algorithms. Nevertheless, most existing Wi-Fi fingerprinting frameworks perform missing-data preprocessing after the RSSI measurements have been transmitted to the server, where preprocessing and inference are executed within the cloud environment [19], [20], [21], [22]. However, relying on centralized cloud servers for preprocessing missing signals introduces significant computational overhead and high response latency, especially when

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handling simultaneous localization queries in dense campus environments. Shifting the standardization process directly to the client-side (edge) addresses these limitations by distributing the computational load, mitigating server bottlenecks, and significantly reducing inference latency for real-time tracking. Furthermore, comparative evaluations of conventional machine learning algorithms under an Android-based edge preprocessing workflow remain relatively limited in real-time lecturer localization scenarios[23], [24], [25].

To address this gap, this study proposes an Android-based edge preprocessing framework for Wi-Fi fingerprinting in which missing RSSI values caused by AP Churn are standardized into -100 dBm directly on the Android client before being transmitted to the cloud inference server. This preprocessing strategy ensures that the RSSI representation used during real-time inference remains consistent with the feature representation employed during model training. Subsequently, four widely used machine learning algorithms, namely Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbor (K-NN), are comparatively evaluated to identify the most suitable classifier for real-time lecturer localization [26], [27], [28], [29].

The main contribution of this study is not the introduction of a new standardization algorithm, but the implementation of an Android-based edge preprocessing workflow that standardizes missing RSSI values before cloud inference and evaluates its effectiveness through comparative machine learning models in a real-time lecturer localization system. The primary objective of this study is to evaluate an Android-based edge preprocessing framework that standardizes missing RSSI values before cloud inference, demonstrating its practicality and efficiency in a real-time lecturer localization system without altering the core machine learning models. [30], [31], [32], [33], [34].

METHODS

To ensure a structured approach, the methodology is divided into data collection, system design, machine learning modeling, and mobile application development. The overall research framework and system architecture are illustrated in Figure 1, which encompasses three sequential stages: (1) Spatial Data Collection, (2) Cloud-Based Model Training, and (3) Real-Time Mobile Edge Deployment.[17], [22], [29].

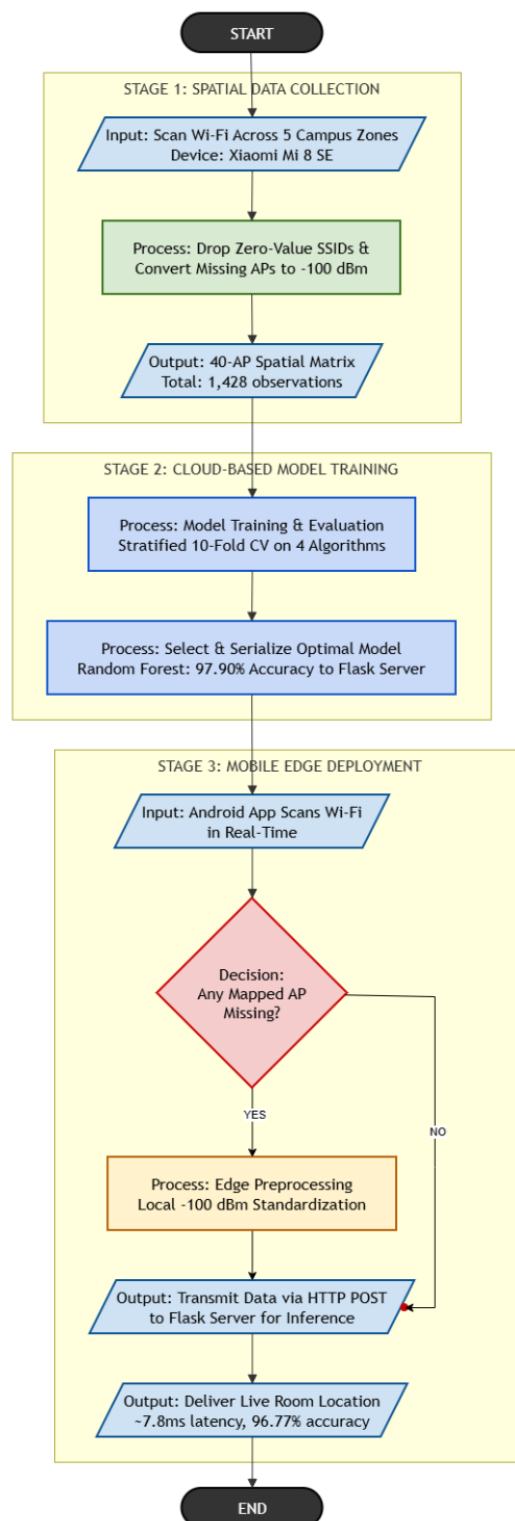


Figure 1. Proposed research framework and system workflow illustrating spatial data collection, cloud-based model training, and real-time mobile edge deployment

Data collection and dataset features

The dataset was constructed through extensive site surveying at Politeknik Caltex Riau, capturing 1,428 observations across 5 target areas frequently used by lecturers: Lab 136, Lab 135, Lab 137, Lab 138, and the connecting corridors.[3], [4]. The spatial data collection was conducted during the late afternoon (approximately 16:00) when student and faculty activities had minimized, ensuring a stable baseline signal

environment.[30]. A Xiaomi Mi 8 SE Android smartphone was utilized as the standard scanning device. At each predefined mapping point, the device recorded Wi-Fi RSSI signals with a stationary scanning duration of approximately 1 minute per data point. Furthermore, to maintain data integrity, the data collection logic was configured to exclusively record active signals, intentionally dropping SSID entries with zero values.[11], [13]. The dataset exhibits a natural class imbalance reflecting the physical topology and spatial volume of the facility: Lab 136 (697 samples), Lab 135 (331 samples), Lab 137 (301 samples), the connecting corridors (79 samples), and Lab 138 (20 samples).[31], [33]. The device recorded RSSI values from 40 distinct Access Points (APs). Table 1 illustrates a subset of the actual dataset to visualize the input features.

Table 1. A sample subset of the Wi-Fi fingerprinting dataset illustrating RSSI features and target lecturer zones

Label_Ruangan	Hafizahss 22:16:d8:c4 :dd:ce (dBm)	PCR-SLX 4c:d6:29:12:03:90 (dBm)	STKgw c0:06:c3:33:3b:6a (dBm)
lab 136	-36	-78	-100
lab 136	-25	-79	-100
lorong	-85	-65	-90

Machine learning pipeline (Model development)

The model creation phase was conducted in a Python environment. The raw dataset was preprocessed using a -100 dBm standardization strategy. It is critical to clarify that -100 dBm is not an arbitrary imputation value, but rather a fixed sentinel value denoting an undetected Access Point (AP) where the signal is completely lost.[11], [13], [29], [32]. To ensure experimental reproducibility and to properly handle the severe spatial class imbalance, the dataset was partitioned using a Stratified 10-Fold Cross-Validation strategy [31], [33]. Furthermore, specific hyperparameters were tuned for optimal performance: the K-Nearest Neighbor model was configured with K=4[35], while the Random Forest ensemble utilized *n_estimators=100*, *max_depth=None*, and explicitly incorporated *class_weight='balanced'* to prevent minority spatial zones from being misclassified[5], [31], [33]. Four algorithms—Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbor (K-NN)—were trained on the 40 RSSI features[7], [8], [16], [27], [28]. The models were comprehensively evaluated using accuracy, precision, recall, F1-score, and confusion matrices to critically assess their performance on the imbalanced spatial dataset[34]. The output of this stage is a serialized classification model capable of mapping signal vectors to physical rooms.

Android application development

The mobile application was developed using Kotlin. It functions as the Edge computing node.[19], [24], [26]. The application handles two primary threads: the Wi-Fi Manager for continuous background RSSI scanning, and the Standardization Engine for formatting the payload before triggering HTTP POST requests to the inference server [17], [25], [29]

RESULT AND DISCUSSION

The experimental evaluation of the proposed Edge-Level Standardization framework was conducted through a comprehensive, multi-stage analytical pipeline. This includes exploratory data analysis, signal variance profiling, dimensionality reduction, multi-model benchmarking, diagnostic error analysis, and validation via real-time mobile edge inference.

Exploratory data analysis (EDA) on lecturer zones

An initial signal variance analysis revealed significant attenuation and overlapping zones between adjacent laboratories and corridors. The high volatility of indoor Wi-Fi signals caused by physical obstructions confirms that simple threshold-based positioning cannot accurately pinpoint a lecturer's room, validating the need for non-linear machine learning classifiers[4], [16], [30].

Dimensionality reduction and spatial clustering

A critical concern when replacing missing data with a static extreme value (-100 dBm) is the potential distortion of the spatial fingerprints. To validate that the Edge-Level Standardization does not corrupt the structural integrity of the radio map, a 2D Principal Component Analysis (PCA) was performed[5], [15].



Figure 2. 2D PCA clustering illustrating the structural integrity and separability of the imputed spatial fingerprints

Figure 2 demonstrates that despite the aggressive edge-level standardization strategy, the high-dimensional 40-AP RSSI matrix successfully compresses into two principal components that form distinct, non-overlapping spatial clusters (e.g., Lab 135, Lab 136, and the corridor). This indicates that the physical characteristics of the radio waves remained structurally valid for high-level classification[29].

Router feature importance ranking

Evaluating the network infrastructure reveals that not all 40 routers contribute equally to the positioning accuracy. A Feature Importance analysis utilizing the Random Forest algorithm was conducted to rank the physical influence of each router[4], [5].

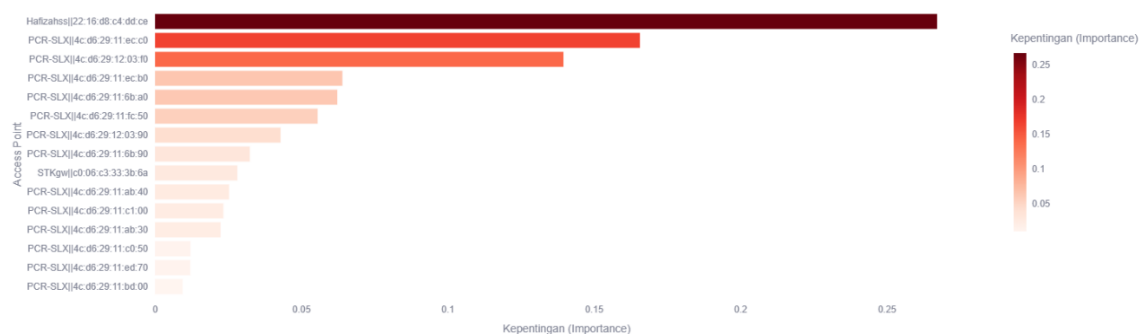


Figure 3. Feature importance ranking highlighting the most critical Access Points for spatial prediction

As depicted in Figure 3, the Access Point identified by the MAC Address Hafizahss||22:16:d8:c4:dd:ce possesses the highest discriminative power, significantly outpacing other routers in the vicinity. This finding indicates that a small, strategically placed subset of routers dictates the vast majority of the localization accuracy within the facility, offering potential avenues for future infrastructure optimization by disabling redundant Aps[4].

Machine learning performance

A comprehensive benchmarking evaluation was conducted to determine the most reliable algorithm for the imputed spatial data.

Table 2. Performance comparison of machine learning algorithms

Algorithm	Accuracy	F1-Score
Random Forest (RF)	97.90%	97.86%
Decision Tree (DT)	96.50%	96.49%
Support Vector Machine (SVM)	96.50%	96.35%
K-Nearest Neighbor (K-NN)	95.10%	95.03%

The findings indicate that the Random Forest algorithm achieved the highest performance. Its F1-Score of 97.86% demonstrates robust capability in resolving spatial blind spots and accurately separating overlapping boundary areas (such as doorways connecting labs to corridors), ensuring the lecturer's location is precisely identified without false bleeding into adjacent rooms [35].

As shown in Table 2, the Random Forest (RF) algorithm achieved exceptional performance, leading the leaderboard with 97.90% accuracy and an F1-Score of 97.86%. The high F1-Score is particularly important, demonstrating that RF minimized both false positives and false negatives despite the severe sample disparity between large rooms like Lab 136 (697 samples) and smaller rooms like Lab 138 (20 samples) [32], [34]. Decision Tree and SVM performed comparably well, both achieving 96.50% accuracy, though DT held a slight edge in F1-Score resilience. K-NN, while computationally lightweight, yielded the lowest performance at 95.10%, as distance-based algorithms are often highly sensitive to identical extreme penalty values (-100 dBm) resulting from standardization [35].

The superior performance of the Random Forest algorithm can be attributed to its ensemble learning mechanism, which combines multiple decision trees to improve robustness against noisy RSSI measurements and missing signal conditions represented by the standardized -100 dBm value. This characteristic enables Random Forest to generalize more effectively than single-tree classifiers when handling spatial variations caused by AP Churn. In contrast, the K-Nearest Neighbor algorithm relies heavily on distance calculations, making it more sensitive to identical penalty values introduced during preprocessing. Decision Tree and Support Vector Machine achieved competitive performance; however, Random Forest demonstrated better discrimination in transitional areas such as corridors where overlapping Wi-Fi fingerprints frequently occur. These findings are consistent with previous studies reporting the effectiveness of ensemble learning for complex indoor localization environments [31], [33], [35].

Diagnostic error analysis

Beyond the macro metrics, a diagnostic error analysis utilizing confusion matrices provides deeper insights into the classifiers' behaviors in spatial blind spots and overlapping boundary areas (such as doorways connecting labs to corridors).

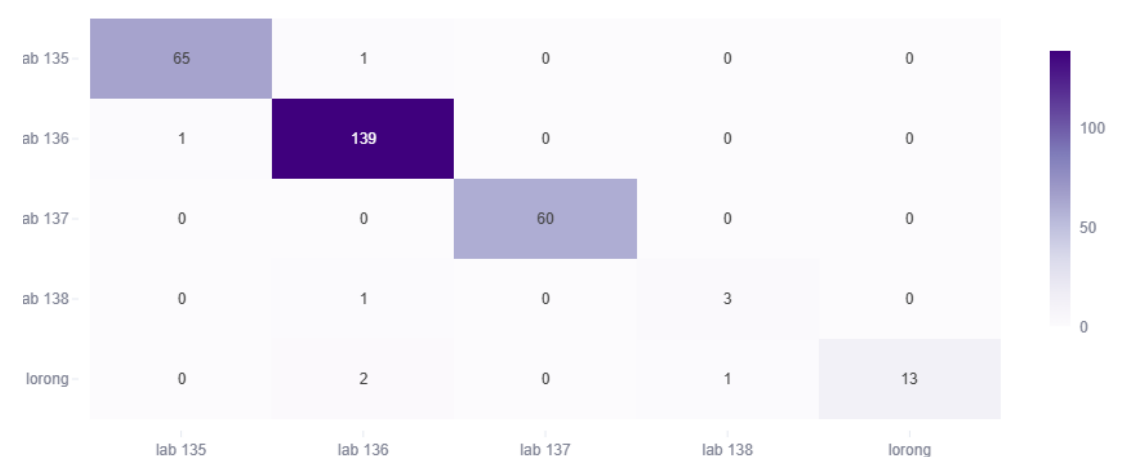


Figure 4. Confusion matrix of the optimal random forest algorithm detailing spatial classification boundaries

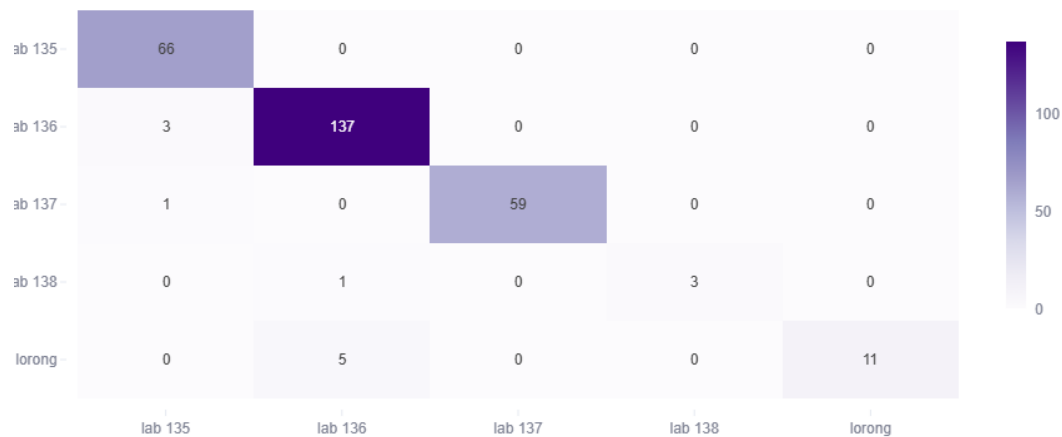


Figure 5. Confusion matrix of the Support Vector Machine (SVM) highlighting higher misclassification rates in boundary areas

Figures 4 and 5 contrast the predictive behavior of Random Forest against SVM. The Random Forest ensemble (Figure 4) demonstrated superior capability in resolving spatial "blind spots." For the highly dynamic minority class 'lorong' (corridor), RF correctly classified the vast majority of instances with minimal bleeding into adjoining laboratories. In contrast, SVM (Figure 5) struggled significantly with the spatial boundaries of the corridor, misclassifying a higher volume of corridor instances into Lab 136 and Lab 137, yielding a much lower recall for that specific transitional area. RF's ensemble averaging effectively captured the complex, nonlinear relationships of the signal overlap near doorways [31], [33].

The confusion matrix analysis further indicates that most classification errors occurred in corridor areas, which naturally exhibit overlapping RSSI characteristics due to their proximity to multiple laboratories. Despite these challenging transition zones, Random Forest maintained higher classification consistency than SVM by reducing misclassification into adjacent rooms. This observation suggests that ensemble-based classifiers are more capable of modeling the nonlinear spatial relationships commonly encountered in practical Wi-Fi fingerprinting environments.

System testing (Real-time mobile inference)

To validate the framework, real-world system testing was conducted by navigating a smartphone equipped with the custom Android application through the targeted campus zones. The edge preprocessing module successfully standardized missing RSSI values into -100 dBm on the Android client before transmitting the fingerprint data to the cloud inference server[17], [22], [29].



Figure 6. Android application interface demonstrating on-device training completion



Figure 7. Real-time spatial tracking interface pinpointing the lecturer's location inside Lab 136

The real-time experiment confirmed that the developed Android application successfully transmitted preprocessed Wi-Fi fingerprint data to the cloud inference server and displayed the predicted lecturer location in real-time. The live tracking test demonstrated that the application could request and receive predictions with a minimal latency of approximately 7.8 milliseconds per inference request[17], [23]. The system achieved a testing accuracy of 96.77%, indicating that the proposed Android-based edge preprocessing workflow can be effectively integrated into practical indoor lecturer localization applications. However, a marginal 1.13% accuracy drop was observed during this live deployment compared to the offline training performance (97.90%). This minor gap highlights several research limitations, primarily the dynamic environmental conditions not captured in the static dataset, such as human body shadowing (signal attenuation when the lecturer holds the device), transient physical obstacles like moving students, and inherent Wi-Fi antenna variations across different smartphone models[3], [6], [30].

CONCLUSION

This study presented an Android-based edge preprocessing framework for Wi-Fi fingerprinting that standardizes missing RSSI values before cloud inference. Experimental evaluation demonstrated that the proposed workflow can be effectively integrated into a real-time lecturer localization system. Among the evaluated classifiers, Random Forest achieved the best performance with 97.90% accuracy, which was rigorously validated using Stratified 10-Fold Cross-Validation and the F1-Score metric to account for spatial imbalance. The results indicate that performing RSSI preprocessing on the Android client provides a practical workflow for real-time indoor positioning without requiring modifications to the trained machine learning models. This study was evaluated in a single educational building and utilized a specific smartphone device model; therefore, future work should investigate the proposed framework across multiple buildings, utilize diverse mobile devices to account for hardware variability, and explore more diverse indoor environments to further validate its generalizability.

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