

AQU-WiFiLoc: Context-Aware Indoor Localization Based on WiFi Fingerprinting

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Abstract—This paper presents **AQU-WiFiLoc**, a context-aware indoor localization framework that augments Received Signal Strength Indicator (RSSI) based conventional Wi-Fi fingerprinting with Cisco Access Point (AP) telemetry and magnetic field signatures. A multi-modal dataset containing 1,343 fingerprints was collected from 14 rooms distributed across two floors of the Faculty of Engineering at Al-Quds University, Palestine.

Initial experiments showed that all evaluated classifiers achieved perfect classification performance under clean conditions, indicating that the collected radio map provides highly discriminative room-level fingerprints. To evaluate robustness under more realistic operating conditions, additive Gaussian noise was introduced exclusively into test-set RSSI values while auxiliary contextual features remained unchanged. Four machine learning classifiers and six feature configurations were evaluated under progressively increasing RSSI degradation.

Results demonstrate that contextual information significantly improves localization robustness. The proposed Context-Aware configuration achieved a macro F1-score of 98.5% using K-Nearest Neighbors under severe noise conditions with standard deviation of 10 dBm, outperforming the RSSI-only baseline. In addition, AP telemetry provided the strongest individual performance gain, highlighting the value of network-side context for robust indoor positioning.

Index Terms—Indoor Localization, Wi-Fi Fingerprinting, RSSI, AP Telemetry, Magnetic Fingerprinting, Machine Learning, Context-Aware Localization.

I. INTRODUCTION

Indoor localization has become an essential enabling technology for smart campuses, healthcare systems, asset tracking, emergency response, and location-based services [1] [2] [3]. While Global Navigation Satellite Systems (GNSS) provide reliable positioning outdoors, signal attenuation and severe multipath propagation make them ineffective in indoor environments [4].

Among the various indoor positioning technologies, Wi-Fi fingerprinting remains one of the most widely adopted approaches because it leverages existing wireless infrastructure and commodity smartphones. Early systems such as RADAR [5] and Horus [6] demonstrated that indoor locations can be distinguished using unique Received Signal Strength Indicator (RSSI) patterns. Large benchmark datasets such as UJIIndoorLoc [7] further accelerated research in Wi-Fi-based localization, while recent machine learning approaches have

achieved high classification performance under controlled conditions [8], [9].

While high localization accuracy is frequently reported under controlled experimental settings, such results do not necessarily reflect real-world deployment scenarios. In practice, localization systems operate in dynamic radio environments where human movement, signal obstruction, multipath fading, interference, and varying network conditions cause substantial RSSI fluctuations. Consequently, fingerprints collected during the offline phase may differ significantly from those observed during operational use. This challenge is particularly important because high localization performance under ideal conditions may conceal significant degradation once RSSI measurements are exposed to realistic environmental variations. Previous studies have shown that RSSI noise and signal fluctuations can substantially reduce the robustness and accuracy of fingerprint-based indoor localization systems [10].

Modern enterprise wireless infrastructures expose additional network-side information that may provide valuable contextual cues for localization. Cisco Access Points (APs), for example, report telemetry measurements such as channel utilization, client count, operating frequency, and channel width. Unlike RSSI, these features characterize network behavior and may remain informative even when radio signals become unstable. Similarly, magnetic field signatures generated by structural elements and electrical installations provide location-dependent fingerprints that are largely independent of wireless signal conditions.

Motivated by these observations, this paper proposes **AQU-WiFiLoc**, a context-aware indoor localization framework that integrates Wi-Fi fingerprints with AP telemetry and magnetic field measurements. The proposed framework investigates whether network-side and environment-side contextual information can improve localization robustness under severe RSSI degradation.

The main contributions of this work are summarized as follows:

- Development of **AQU-WiFiLoc**, a context-aware indoor localization framework that integrates Wi-Fi RSSI, enterprise AP telemetry, and magnetic field signatures.
- Collection of a multi-modal indoor localization dataset comprising 1,343 fingerprints collected from

14 rooms within a Cisco-managed university environment.

- Robustness assessment through controlled test-set noise injection while preserving training data integrity.
- Systematic evaluation of six feature configurations using four machine learning classifiers under progressive RSSI degradation.
- Experimental validation that AP telemetry and magnetic anchoring improve localization performance under noisy operating conditions.

The literature reveals two important gaps in current Wi-Fi fingerprinting research. First, most existing localization systems continue to rely primarily on RSSI measurements despite the availability of richer contextual information from modern enterprise WLAN infrastructures. Second, robustness under degraded RF conditions remains insufficiently investigated, with many studies reporting performance only under static or near-ideal environments.

To address these limitations, the proposed framework integrates enterprise AP telemetry and magnetic anchoring within a unified feature space and evaluates localization robustness under controlled RSSI degradation.

II. RELATED WORK

Indoor localization has been extensively investigated over the past two decades, with Wi-Fi fingerprinting emerging as one of the most practical approaches due to its reliance on existing wireless infrastructure. Research efforts have focused on improving localization accuracy, robustness, scalability, and adaptability through probabilistic modeling, machine learning, sensor fusion, and context-aware techniques.

A. Wi-Fi Fingerprinting and Machine Learning

RADAR [5] was among the earliest systems to demonstrate indoor positioning using RSSI fingerprints collected from existing wireless infrastructure. Subsequently, Horus [6] introduced probabilistic signal modeling to address RSSI uncertainty and temporal variability.

To facilitate benchmarking and comparative evaluation, large-scale datasets such as UJIIndoorLoc [7] were introduced, enabling multi-building and multi-floor localization research. More recently, machine learning techniques have become dominant in fingerprint-based localization. Attar et al. [8] demonstrated high classification performance using several machine learning algorithms, while Nessa et al. [9] identified machine learning as one of the most promising directions for indoor positioning research.

Recent studies have also explored advanced learning architectures, including Transformer-based models for robust RSSI representation learning [11] and federated learning frameworks for privacy-preserving localization [12]. Despite these advances, most Wi-Fi fingerprinting systems remain heavily dependent on RSSI measurements, making them vulnerable to environmental dynamics, multipath fading, interference, and network congestion.

B. Sensor Fusion and Magnetic Localization

To overcome the limitations of RSSI-only fingerprinting, researchers have investigated the integration of complementary sensing modalities. Among these, magnetic field measurements are particularly attractive because they are generated by structural elements, electrical wiring, and metallic infrastructure, producing location-dependent signatures that remain relatively stable over time.

Ouyang and Abed-Meraim [13] provided a comprehensive review of magnetic-field localization techniques and highlighted their potential for improving indoor positioning accuracy. Similarly, Sarcevic et al. [14] demonstrated that combining RSSI and magnetic fingerprints can improve localization performance compared with Wi-Fi-only approaches.

Although magnetic anchoring provides valuable environmental context, it is typically studied independently from network-side information.

C. Network-Aware Localization

Recent studies have emphasized the importance of contextual information beyond conventional RSSI measurements. Koutsonikolas et al. [15] demonstrated that smartphone-based wireless scans can capture useful information regarding channel usage and network activity. Yin et al. [16] proposed adaptive radio-map maintenance techniques to mitigate temporal changes in wireless environments, while Manzoor et al. [17] investigated resource-aware wireless optimization.

These studies indicate that network behavior contains valuable contextual information. However, enterprise AP telemetry measurements such as channel utilization, client count, and channel width have rarely been treated as explicit localization features. Furthermore, the joint use of network-side telemetry and magnetic anchoring remains largely unexplored in Wi-Fi fingerprinting literature.

III. PROPOSED METHODOLOGY

A. Framework Overview

The proposed AQU-WiFiLoc framework extends conventional Wi-Fi fingerprinting by integrating network-side contextual information obtained from Cisco Access Points (APs) and environment-side contextual information derived from smartphone magnetic sensors.

Figure 1 illustrates the overall workflow of the proposed framework.

The framework consists of four sequential stages, starting from multi-modal data acquisition and ending with room-level classification under controlled RSSI degradation:

- 1) Multi-modal data acquisition using a custom Android application.
- 2) Radio-map construction and feature extraction.
- 3) Context-aware feature fusion.
- 4) Room-level classification using machine learning algorithms.

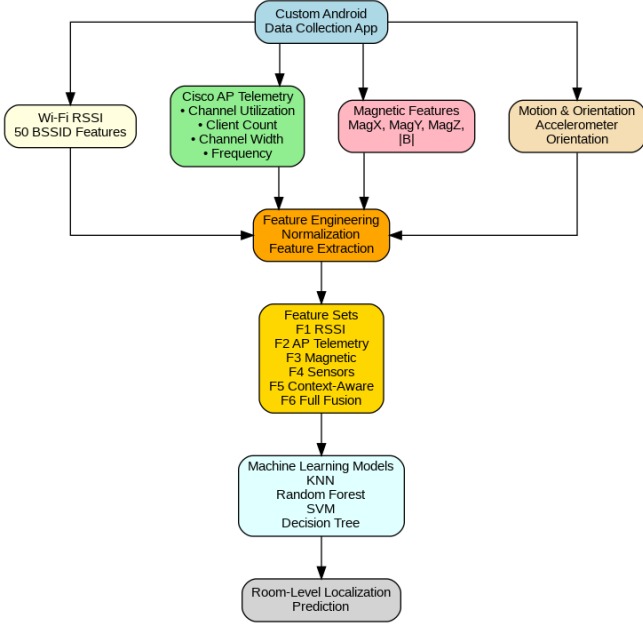


Fig. 1. Architecture of the proposed AQU-WiFiLoc framework.

B. Data Collection Environment and Conditions

Data collection was conducted within the Faculty of Engineering at Al-Quds University, Palestine. The study environment consists of 14 rooms distributed across two floors and covered by a Cisco-managed wireless infrastructure operating under the AL-QUDS-WLAN and eduroam networks. The selected rooms include classrooms, laboratories, and offices with varying spatial layouts and AP visibility conditions.

A custom Android application was developed and deployed on a Samsung SM-A135F smartphone running Android 14. For each room, the operator continuously moved throughout the environment for approximately three minutes while Wi-Fi scans and sensor measurements were recorded every two seconds. This procedure ensured that fingerprints captured spatial variations caused by room geometry, wall attenuation, local fading, and AP visibility rather than a single static position.

Data collection was conducted during the final days of the academic semester when student presence was minimal. This decision was intentionally made to construct a stable baseline radio map with limited human-induced signal fluctuations. Under these low-occupancy conditions, the collected RSSI patterns primarily reflect structural characteristics of the environment, including room geometry, wall attenuation, and AP placement, rather than temporary crowd-related effects. Consequently, the resulting radio map exhibits higher reproducibility and reduced measurement uncertainty during the offline fingerprinting phase.

To evaluate operational robustness while preserving a consistent reference radio map, a controlled RSSI perturbation methodology was adopted instead of conducting a second site survey under different occupancy conditions. This approach enables systematic assessment of localization performance under increasing signal degradation

TABLE I
DATASET STATISTICS

Property	Value
Rooms	14
Floors	2
Fingerprints	1,343
Wi-Fi Records	14,927
Unique BSSIDs	50
Average APs per Scan	11.1
Collection Device	Samsung SM-A135F
Collection Interval	2 s
Official SSIDs	AL-QUDS-WLAN, eduroam
Infrastructure	Cisco

while avoiding temporal inconsistencies between training and evaluation datasets. The noise injection procedure is described in Section IV-B.

C. Dataset Construction

Initially, 20,508 Wi-Fi scan records were collected. After removing non-institutional access points, 14,927 valid records remained. Multiple Wi-Fi observations belonging to the same scan event were grouped using a unique ScanID and aggregated into a single fingerprint representation.

As a result, the final dataset contains 1,343 fingerprints representing room-level observations used for machine learning experiments. Each fingerprint represents a single scan event aggregated from all Wi-Fi observations collected within the corresponding acquisition interval.

On average, each fingerprint contains measurements from 11.1 detected access points selected from a total of 50 unique BSSIDs observed throughout the environment.

Table I summarizes the resulting dataset.

D. Feature Engineering

A radio map containing 50 BSSID-based RSSI features was constructed from the collected fingerprints. Undetected access points were assigned a default value of -105 dBm to ensure a fixed-length feature representation across all fingerprints.

In addition to RSSI fingerprints, contextual features were extracted from AP telemetry and smartphone sensors. These categories were intentionally designed to capture complementary information from RF signals, network behavior, environmental signatures, and device sensing modalities.

The complete feature space was divided into four categories:

- 1) RSSI Radio Map Features
- 2) AP Telemetry Features
- 3) Magnetic Features
- 4) Motion and Orientation Features

1) *AP Telemetry Features*: Enterprise Cisco Access Points expose several network-state indicators that characterize channel usage and user activity.

The extracted telemetry features include:

- Mean Channel Utilization
- Maximum Channel Utilization
- Mean Client Count
- Maximum Client Count

- Mean Operating Frequency
- Mean Channel Width
- Connected Channel

Unlike RSSI measurements, these features describe network behavior rather than signal strength and therefore provide complementary contextual information.

2) *Magnetic Features*: Magnetic signatures were extracted from the smartphone magnetometer.

For each fingerprint, the three magnetic axes (B_x, B_y, B_z) were recorded together with the magnetic field magnitude:

$$\|B\| = \sqrt{B_x^2 + B_y^2 + B_z^2} \quad (1)$$

Magnetic fingerprints are largely independent of wireless propagation effects and remain relatively stable over time.

3) *Motion and Orientation Features*: Accelerometer measurements were represented using their three Cartesian axes and signal magnitude.

Orientation measurements were encoded using sine and cosine transformations to eliminate angular discontinuities:

$$f(\theta) = [\sin(\theta), \cos(\theta)] \quad (2)$$

E. Feature Design Rationale

A key methodological contribution of this work is the deliberate exclusion of RSSI-derived statistical features such as MeanRSSI, MaxRSSI, MinRSSI, RSSI variance, and visible AP counts.

Preliminary experiments demonstrated that these statistics become highly sensitive to RSSI perturbations and introduce significant distribution shift between training and testing domains.

Consequently, only RSSI-independent contextual features were included in the auxiliary feature groups, ensuring that AP telemetry and magnetic measurements contribute genuinely complementary information.

While AP telemetry and sensor measurements may also vary under different occupancy conditions, these variations represent meaningful environmental and network context rather than direct corruption of the RF signal. In contrast, RSSI is the primary feature affected by multipath fading, interference, and human-body shadowing. Consequently, perturbations were applied exclusively to RSSI measurements in order to evaluate whether contextual features can compensate for degraded radio conditions while preserving their physical interpretability.

F. Feature Configurations

To quantify the contribution of each modality, six feature configurations were evaluated. Table II summarizes the feature sets and their corresponding dimensions.

Among these configurations, F5 represents the proposed AQU-WiFiLoc framework. It combines network-side context obtained from Cisco AP telemetry with environment-side context derived from magnetic anchoring while avoiding additional low-discriminative motion features.

TABLE II
FEATURE CONFIGURATIONS

Feature Set	Dimension	Description
F1	50	RSSI Only
F2	57	RSSI + AP Telemetry
F3	54	RSSI + Magnetic
F4	64	RSSI + Magnetic + Motion + Orientation
F5	61	RSSI + AP Telemetry + Magnetic
F6	71	Full Fusion

Consequently, F5 was selected as the primary proposed configuration because it combines network-side and environment-side contextual information while maintaining a compact feature representation.

IV. EXPERIMENTAL SETUP

A. Training and Testing Strategy

The dataset was partitioned using a stratified 70/30 hold-out strategy to preserve class balance across all room labels. The resulting split contained 941 training fingerprints and 402 testing fingerprints. To prevent data leakage, the partitioning process was performed before any noise injection or normalization steps.

All experiments were implemented in MATLAB using a fixed random seed (`rng(42)`) to ensure reproducibility.

B. Noise Injection

To evaluate localization robustness under realistic wireless conditions, additive white Gaussian noise (AWGN) was injected exclusively into the RSSI values of the testing partition

$$\tilde{R}_{test} = R_{test} + \epsilon \quad (3)$$

where the AWGN ϵ is with zero-mean and variance σ^2

$$\epsilon \sim \mathcal{N}(0, \sigma^2)$$

and the standard deviation σ is selected as

$$\sigma \in \{0, 2, 4, 6, 8, 10\} \text{ dBm}$$

The validity of the noise injection procedure was verified empirically at $\sigma = 10$ dBm. The observed noise standard deviation was 9.68 dBm (error < 3.2%) with a mean bias of +0.14 dBm. Noise was applied only to detected RSSI values, while missing AP entries (-105 dBm) remained unchanged.

The adopted strategy intentionally perturbs only the testing partition to emulate a practical deployment scenario in which a radio map is collected under controlled conditions while localization is performed later under dynamic wireless environments. This approach also prevents the classifiers from adapting to the injected noise distribution, providing a more realistic assessment of robustness.

C. Normalization Strategy

RSSI and auxiliary features were normalized separately using training-set z-score parameters, preventing scale imbalance between RSSI and contextual features.

D. Machine Learning Models

Four machine learning classifiers were evaluated:

- K-Nearest Neighbors (KNN, $K = 7$)
- Random Forest (200 trees)
- Support Vector Machine (RBF Kernel)
- Decision Tree

These classifiers were selected to represent different learning paradigms commonly used in Wi-Fi fingerprinting, including distance-based, ensemble-based, margin-based, and rule-based classification.

Macro F1-score was selected as the primary performance metric because it equally weights all room classes and provides a balanced evaluation under noisy operating conditions. Although classification accuracy was also monitored, Macro F1-score was used as the main criterion for comparing feature configurations and models.

V. RESULTS AND DISCUSSION

A. RSSI Robustness Analysis

Under clean conditions ($\sigma = 0$ dBm), all evaluated classifiers achieved a macro F1-score of 100%, indicating that the collected radio map provides highly discriminative room-level fingerprints.

While these results confirm the quality of the dataset, they also limit the ability to distinguish between competing feature configurations under ideal conditions. Therefore, controlled RSSI perturbations were introduced to emulate realistic wireless degradation scenarios and evaluate the robustness contribution of contextual features.

Figure 2 illustrates the performance degradation of RSSI-only fingerprinting under increasing noise levels.

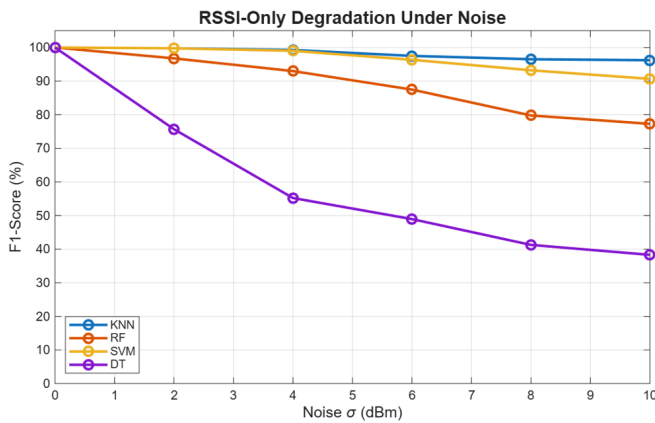


Fig. 2. Performance degradation of RSSI-only fingerprinting under increasing Gaussian noise.

Among the evaluated models, KNN demonstrated the highest robustness, whereas Decision Tree exhibited the strongest sensitivity to signal perturbation. These observations highlight the importance of evaluating localization systems under degraded RF conditions rather than relying solely on performance measured under ideal environments.

B. Feature Configuration Analysis

Table III summarizes the macro F1-score obtained under the most challenging condition ($\sigma = 10$ dBm).

TABLE III
MACRO F1-SCORE (%) AT $\sigma = 10$ dBm

Feature Set	KNN	RF	SVM	DT
F1 RSSI Only	96.5	73.3	92.3	39.6
F2 AP Telemetry	98.0	86.3	95.9	51.7
F3 Magnetic	97.3	74.6	95.9	39.6
F4 Sensors Fusion	96.0	76.8	96.5	39.6
F5 Context-Aware	98.5	88.5	97.2	51.7
F6 Full Fusion	96.9	86.6	96.8	51.7

F6 does not outperform F5 despite using a larger feature set, indicating that Motion and Orientation measurements provide limited discriminative information for room-level localization.

The results demonstrate that contextual information substantially improves localization robustness under RSSI degradation. The proposed F5 configuration achieved the highest overall performance and delivered the most consistent gains across the evaluated classifiers, confirming the complementary contribution of AP telemetry and magnetic anchoring.

Figure 3 highlights the performance gains achieved by the contextual feature configurations relative to the RSSI-only baseline at $\sigma = 10$ dBm, with F5 providing the largest overall improvement.

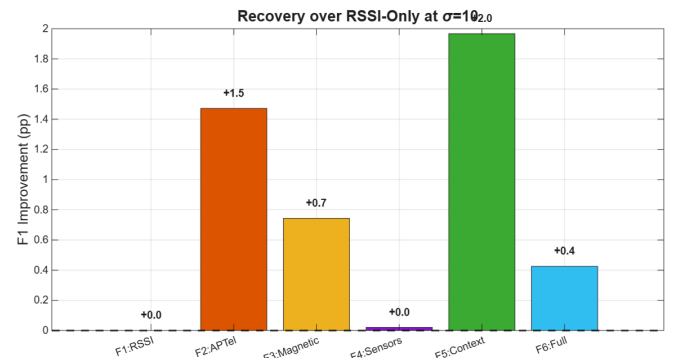


Fig. 3. F1-score Performance improvement relative to the RSSI-only baseline at $\sigma = 10$ dBm.

C. Recovery Gain Analysis

To quantify the contribution of contextual information, Table IV compares the RSSI-only baseline (F1) with the proposed Context-Aware configuration (F5).

TABLE IV
RECOVERY GAIN OF F5 OVER RSSI-ONLY BASELINE

Model	F1	F5	Gain
KNN	96.5	98.5	+2.0
RF	73.3	88.5	+15.2
SVM	92.3	97.2	+4.9
DT	39.6	51.7	+12.1

The largest improvement was observed for Random Forest, which recovered 15.2 percentage points. This result indicates that AP telemetry and magnetic features provide complementary information capable of compensating for RSSI degradation.

It is noteworthy that all feature configurations achieved nearly identical performance under clean conditions. Therefore, the observed gains under RSSI degradation do not represent improvements in baseline accuracy, but rather improvements in robustness when radio conditions become unstable.

D. Effect of AP Telemetry

Among all individual feature groups, AP telemetry provided the strongest performance gain, exceeding the contribution of magnetic and sensor-based features.

Channel utilization, client count, and channel characteristics contain location-dependent information that remains informative even when RSSI measurements become unstable.

This finding suggests that enterprise wireless infrastructure can provide valuable contextual features for indoor localization at no additional deployment cost.

E. Radio Map Visualization

Figure 4 presents the generated radio map and highlights the spatial diversity of RSSI fingerprints across rooms.

The observed fingerprint diversity explains the perfect classification performance obtained under clean conditions and supports the feasibility of room-level localization within the target environment.

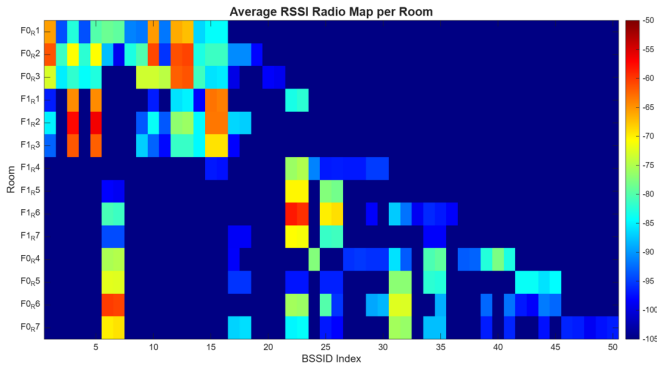


Fig. 4. Average RSSI radio map across the 14 surveyed rooms.

VI. LIMITATIONS AND FUTURE WORK

The proposed framework was evaluated using data collected from a single building and a single smartphone under low-occupancy conditions. Furthermore, robustness was assessed through controlled RSSI perturbations rather than real peak-hour measurements. Future work will explore multi-building environments with large scale dataset, cross-device generalization, deep learning extension, and real-time evaluation under operational campus conditions.

VII. CONCLUSION

This paper presented AQU-WiFiLoc, a context-aware indoor localization framework that combines Wi-Fi fingerprinting with Cisco AP telemetry and magnetic field anchoring.

A multi-modal dataset containing 1,343 fingerprints was collected from 14 rooms within a Cisco-managed

university environment and used to evaluate six feature configurations under progressive RSSI degradation.

Although all evaluated classifiers achieved perfect performance under clean conditions, contextual information significantly improved localization robustness under degraded RSSI measurements.

Experimental results demonstrate that AP telemetry provides the strongest individual contextual contribution, while its combination with magnetic anchoring yields the most robust overall configuration.

The proposed Context-Aware feature set (F5) achieved the best overall performance, reaching 98.5% macro F1-score using KNN under severe noise conditions.

The findings demonstrate that enterprise AP telemetry and magnetic anchoring provide effective contextual information capable of improving the robustness of Wi-Fi fingerprinting systems while preserving the low-cost deployment advantages of existing WLAN infrastructures.

REFERENCES

- [1] S. Mostafa, K. A. Harras and M. Youssef, "A Survey of Indoor Localization Systems for Multi-Floor Environments," *IEEE Access*, vol. 13, pp. 146396-146432, 2025.
- [2] X. Feng, K. An Nguyen and Z. Luo, "A Review of Open Access WiFi Fingerprinting Datasets for Indoor Positioning," *IEEE Access*, vol. 12, pp. 167970-167989, 2024.
- [3] S. Shang and L. Wang, "Overview of WiFi fingerprinting-based indoor positioning," *IET Communications*, vol. 16, no. 7, pp. 725-733, 2022.
- [4] F. Zafari, A. Gkelias, and K. K. Leung, "A survey of indoor localization systems and technologies," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2568-2599, 2019.
- [5] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *Proc. IEEE INFOCOM*, 2000, pp. 775-784.
- [6] M. Youssef and A. Agrawala, "The Horus WLAN Location Determination System," in *Proc. 3rd Int. Conf. Mobile Syst. Serv. (MobiSys)*, 2005, pp. 205-218.
- [7] J. Torres-Sospedra *et al.*, "UJIIndoorLoc: A new multi-building and multi-floor database for WLAN fingerprint-based indoor localization problems," in *Proc. Int. Conf. IPIN*, 2014.
- [8] H. Attar *et al.*, "Machine Learning in Indoor Localization Prediction Using Received Signal Strength Indicator and Wi-Fi Network," *Int. J. Intell. Networks*, vol. 6, pp. 233-243, 2025.
- [9] A. Nessa, B. Adhikari, F. Hussain, and X. N. Fernando, "A survey of machine learning for indoor positioning," *IEEE Access*, vol. 8, pp. 214945-214965, 2020.
- [10] H. Li, Z. Qian, C. Tian, and X. Wang, "TILoc: Improving the Robustness and Accuracy for Fingerprint-Based Indoor Localization," *IEEE Internet of Things Journal*, vol. 7, no. 4, pp. 3053-3066, 2020.
- [11] B. Singh and R. Chatterjee, "ILT: Advancing indoor localization with Transformer learning on Wi-Fi RSSI data," in *Proc. OCIT*, 2025.
- [12] K. Roy *et al.*, "FedWiLoc: Federated learning for privacy-preserving WiFi indoor localization," *arXiv preprint arXiv:2512.18207*, 2025.
- [13] G. Ouyang and K. Abed-Meraim, "A survey of magnetic-field-based indoor localization," *Electronics*, vol. 11, no. 6, p. 864, 2022.
- [14] P. Sarcevic *et al.*, "Indoor 2D positioning based on fusion of RSSI and magnetometer fingerprints," *Sensors*, vol. 23, p. 1855, 2023.
- [15] C. Koutsonikolas *et al.*, "A walk on the client side: Monitoring enterprise WiFi networks using smartphone channel scans," in *Proc. IEEE INFOCOM*, 2016.
- [16] J. Yin *et al.*, "Learning adaptive temporal radio maps for signal strength-based location fingerprinting," *IEEE Trans. Mobile Comput.*, vol. 7, no. 5, pp. 564-576, 2008.
- [17] S. Manzoor *et al.*, "SWIF: Smart Wi-Fi Integration Framework for Mobility and Resource Optimization," *IEEE Access*, vol. 12, pp. 177609-177620, 2024.