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RSSI-BASED INDOOR LOCALIZATION USING WI-FI SIGNALS AND MACHINE LEARNING ALGORITHMS

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Abstract
Indoor localization has become increasingly important in smart buildings, healthcare, logistics, emergency response, and context-aware services, where accurate indoor position information is required but Global Positioning System (GPS) signals perform poorly because of walls, ceilings, and other indoor obstacles. The design and implementation of the indoor localization system that uses Wi-Fi Received Signal Strength Indicator (RSSI) and machine learning techniques is presented in this study. The ultimate goal of the study is to build a feasible, inexpensive and robust indoor localization system that can conveniently estimate the location of a person or device within a building using the current Wi-Fi system. The study is a quantitative experimental design consisting of theoretical modeling, controlled data collection in the laboratory and comparison of algorithms. The theoretical model used is Free Space Path Loss (FSPL) and Log-Normal Shadowing models describing the RSSI behavior in indoor environments. RSSI data were collected from 50 reference points using smartphones and laptops in a controlled indoor environment having three Wi-Fi access points. Evaluation of localization was carried out using trilateration, k-nearest neighbors (k-NN) fingerprinting, Support Vector Machine (SVM), and Random Forest. It is clear that RSSI varies with distance, but is still subject to environmental obstruction, multipath fading, and device variations. SVM got the best performance with a mean localization error of 1.73 m, followed by Random Forest (1.95 m), trilateration (3.12 m) and k-NN fingerprinting (2.21 m). Based on this, it can be concluded that when combined with appropriate preprocessing and intelligent learning algorithms, the RSSI based indoor localization is feasible and affordable, and the SVM algorithm has the best localization performance in the proposed localization system.

INTRODUCTION

The field of indoor localization has emerged as a significant research and engineering topic due to the fact that a significant portion of human activity is now occurring within buildings (universities, hospitals, airports, offices, shopping malls, warehouses and industrial plants). These are the areas where exact location information is essential for navigation, asset tracking, emergency management, safety management, smart services and operational automation. The recent literature shows that the indoor positioning is no

longer a niche topic, but is essentially becoming a basic enabler technology for smart buildings, Industry 4.0 systems and even location-based digital services. Specifically, the accurate information about positioning indoors is now regarded as the key to the management of the resources, the workflows, and the processes that require safety in the contemporary operational settings (Li et al., 2024; Zholamanov et al., 2025).

One of the contributing factors to this increasing interest is the ineffective operation of the satellite-based positioning in confined areas. Global Navigation Satellite System (GNSS) technologies such as GPS are dependable outdoors but the signal is significantly compromised indoors due to walls, ceilings, furniture and other impediments. Moreover, positioning accuracy and consistency are also diminished by multipath propagation, non-line-of-sight conditions and interference. Consequently, the GNSS-based solutions are not sufficient to serve numerous indoor applications that need reliable meter-level positioning. Recent works thus reaffirm that indoor localization is a unique and technically challenging issue, particularly in realistic conditions where the behavior of signals is not as predictable as it would be in an open outdoor scenario (Li et al., 2024; Maduranga et al., 2024).

In a bid to address these shortcomings, researchers have examined various indoor positioning systems such as RFID, Bluetooth Low Energy (BLE), ultra-wideband (UWB), visible light and Wi-Fi. Of these alternatives, localization based on Wi-Fi is particularly appealing, as the Wi-Fi infrastructure is already present in most institutional and commercial buildings, and smartphones and laptops, as well as a lot of IoT devices, can estimate the strength of Wi-Fi connections without requiring costly dedicated equipment. This renders Wi-Fi especially applicable to low cost and scalable implementation. Recent research and reviews indicate that Wi-Fi Received Signal Strength Indicator (RSSI) techniques remain popular due to their affordability, accessibility, and practicability. Also, practical experiments demonstrate that Wi-Fi RSSI can provide indoor navigation and tracking with practical accuracy when used with caution in real situations (Aminah et al., 2024; Zholamanov et al., 2025).

In indoor localization systems based on Wi-Fi, RSSI is considered one of the most popular measurements due to its ease of acquisition by commodity devices, and its ability to be used in distance-based and fingerprint-based localization. In fingerprinting, the RSSI vectors at known reference points are recorded in a radio map, and compared with live measurements to approximate the position of a user. Most recently, machine learning has reinforced this process by training complicated and nonlinear correlation between RSSI patterns and physical locations. Recent studies have demonstrated that machine learning and deep learning techniques can enhance the robustness and accuracy of localization by considering behavior of signals more flexibly than geometric conversion alone. Comparative analyses also verify that various machine-learning models, such as support vector machines and analogous methods, can deliver powerful localization performances in well-organized experimental environments (Nabati and Ghorashi, 2023; Esmaeili Gorjan and Gil Jiménez, 2024; Attar et al., 2025).

Although these breakthroughs have been made, there still are significant technical and practical issues. RSSI values are very susceptible to multipath fading, shadowing, interference, signal drift, device heterogeneity, and environmental variations including door movement, furniture movement, and change in access-point conditions. These may decrease the accuracy of localization as well as render trained models unstable with time. Furthermore, fingerprint systems are in many cases labor intensive in the offline collection of data and in the periodic updates made to keep the performance current. In recent reviews, it is still found that RSSI instability, fingerprint maintenance, and robustness in dynamic environments are some of the significant unresolved issues. This implies that the idea of Wi-Fi RSSI localization has an untapped potential, but it needs meticulous

modeling, preprocessing, and choice of algorithms to be converted into a practical tool that could be used in a reliable real-world setting (Chia et al., 2025; Maduranga et al., 2024; Zholamanov et al., 2025).

Research Gap

The recent literature indicates that there has been an evident advancement in Wi-Fi RSSI indoor localization especially in fingerprinting, preprocessing, and machine-learning-based estimation. Yet, there are still a number of gaps. To begin with, most of the published practices are effective under controlled conditions but their versatility in natural indoor settings remains possible. Second, fingerprint database creation and refresh is still expensive and time consuming. Third, the literature continues to be deficient of sufficient practical research that would compare the classical algorithms like trilateration and k-nearest neighbors fingerprinting algorithms with machine-learning algorithms in the same controlled experimental environment using commodity Wi-Fi equipment. Lastly we have yet to see a universally acceptable low-cost model that can be at once accurate, robust, easy to implement and practically interpretable. Thus, there is still a need to have realistic and experimentally-supported research that studies the RSSI behavior, a localization model that is based on RSSI, and compares directly traditional and machine-learning-based approaches in the same indoor scenario.

The aim of this study is to develop a system that can accurately determine the location of a person or device inside a building using Wi-Fi-based signals, particularly RSSI measurements. In doing so, the study seeks to design a practical, low-cost, and reliable indoor localization framework that combines wireless signal analysis with suitable localization techniques and machine learning methods. The ultimate goal is to provide an indoor location estimation solution deployable to real environments without GPS coverage, in which existing Wi-Fi infrastructures can be utilized efficiently to estimate location.

Research Objectives

The study pursues the following objectives:

This Study aims to understand and analyze RSSI signal behavior in indoor environments and develop a model using RSSI values for localization. A positioning methods such as trilateration, fingerprinting, or machine learning will be designed for indoor positioning. Finally, the system's accuracy and reliability will be evaluated across different indoor areas to assess its practical performance.

1. Literature Review

The localization of indoors has become a significant line of research as numerous modern-day services now rely on precise indoor position data where GNSS technologies like GPS cannot be trusted. Indoor navigation, tracking of assets, safety, automation and context-aware services are needed in buildings like hospitals, universities, offices, airports, warehouses, and industrial plants. Recent review literature demonstrates that indoor positioning is becoming more of a basis of smart buildings and Industry 4.0 settings than a localized scholarly issue. Li et al. (2024) highlight that accurate indoor positioning information are the key to organizing industrial resources and processes, and Zholamanov et al. (2025) demonstrate that the focus of the studies in this field is now on signal capture, radiomap generation, preprocessing, model training, and implementation issues.

One of the main themes of the literature is that the outdoor positioning technologies do not port over easily in indoor settings. Walls, ceilings, furniture, equipment and more weaken or block satellite signals, and multipath propagation and non-line-of-sight conditions further distort. Due to these problems, indoor localization has turned into a separate engineering issue necessitating different infrastructure and algorithmic approaches. Even more recent work still supports the idea that indoor environments are difficult, in part, because behaviors of signals are less predictable and stable than in open environments. This is the reason why indoor localization studies have taken a turn into

wireless technologies that may work with the local infrastructure that is already present within buildings.

Wi-Fi is one of the most viable and affordable technologies that have been investigated in terms of indoor positioning. Most institutional and commercial areas already have Wi-Fi access points, commodity devices like smartphones and laptops have the ability to measure Received Signal Strength Indicator (RSSI) values without special equipment. This renders Wi-Fi RSSI especially appealing to low cost scalable localization. Aminah et al. (2024) show that an RSSI-based indoor navigation and tracking can be developed on a fingerprint mapping and k-nearest neighbors with regular smartphones, and more recent reviews reveal that RSSI fingerprinting remains a popular choice due to its cost-efficiency, ease of use, and the ability to work with existing infrastructure. Concurrently, it is evident in the literature that Wi-Fi RSSI cannot be considered as a stable source of signals in the first place. There are significant variability issues associated with its usefulness.

RSSI instability is the primary technical challenge that has been reported in the literature numerous times. Indoor RSSI varies due to multipath fading, shadowing, signal attenuation, interference, access-point geometry, user mobility, device heterogeneity, as well as change in the environment like opening of doors or moving of furniture. According to Maduranga et al. (2024), it becomes extremely difficult to perform accurate localization under these conditions, relying solely on path-loss modeling and using multilateration. Similar results are presented by Chia et al. (2025), who demonstrate that dynamic indoor buildings are still a major unsolved problem due to the high level of instability and interference that drastically changes the RSSI patterns and diminishes the reliability of fingerprint matching. The results are of great importance as they explain the need to not always rely on simple geometric conversion of RSSI to distance in a realistic indoor environment.

Due to the noisiness of the raw RSSI, fingerprinting is now one of the most popular techniques of Wi-Fi indoor localization. In fingerprint-based localization, measurements of RSSI vectors are recorded at known reference points in an offline phase to construct a radiomap, and then compared with measurements of live measurements in an online phase to approximate the location of the user. This is handled in the literature as an effective alternative to pure range-based positioning since it does not attempt to reduce RSSI to a simple distance estimate but uses the complete spatial signal pattern. Fingerprinting is, however, not without its challenges. It needs to have high data density, radiomap design, and maintenance when the environment varies. Yang et al. (2024) state that most of the research pays excessive attention to the online matching phase and underemphasizes the significance of preprocessing the offline fingerprint database. Their Preprocessing method of Fingerprint Dictionary was specifically intended to enhance the localization performance, by ensuring that radio-map data is made smaller and more informative prior to the match occurrence.

The other powerful theme of the recent literature is the expense and the challenge of data collection. Fingerprint systems are very enticing to practice, yet the offline phase is frequently labor-intensive and costly. Several recent studies explicitly tackle this issue. In a 2024 paper on semi-supervised generative adversarial learning, it is emphasized that Wi-Fi fingerprint localization involves manually collecting and labeling data in the positioning area, and that synthetic trainable fingerprint generation is proposed to minimise the effort. Similarly, research on robot-assisted RSSI data collection published in 2025 indicates that automated collection may require significantly less time to collect the data and also be more accurate compared to traditional smartphone-based collection. The significance of these studies is that they demonstrate that the fingerprint database itself is not a mere dataset but a key engineering problem in indoor localization.

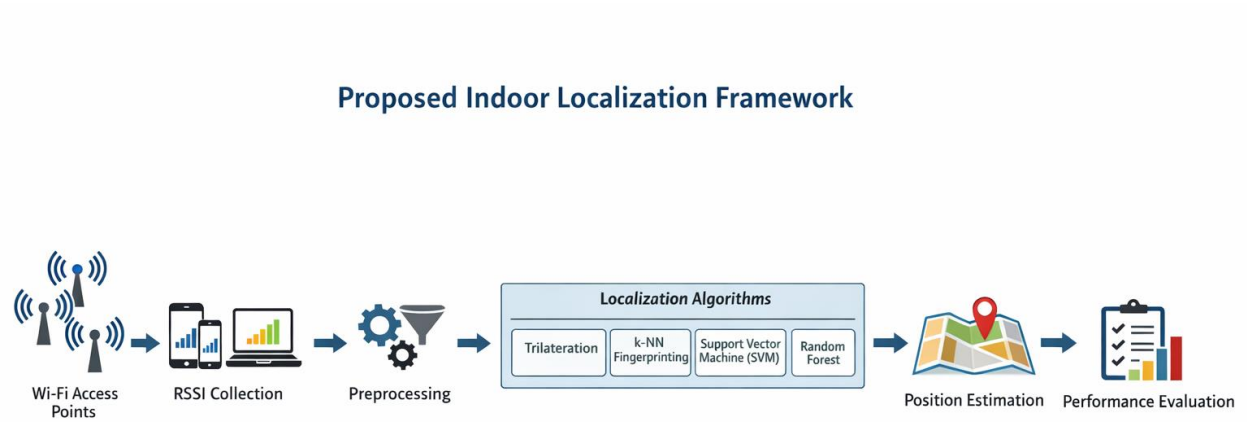
Machine learning has emerged as one of the most powerful research directions in recent Wi-Fi RSSI

localization since it is able to reflect nonlinear and noisy dependencies between signal patterns and physical position compared to simple analytical models. In 2024 and 2025, comparative studies reveal that machine-learning pipelines have become typical to include data cleansing, feature tuning, feature selection, and classifier or regressor comparison. Esmaeili Gorjan and Gil Jiménez (2024) demonstrate that machine-learning algorithms can enhance the localization of an indoor Wi-Fi network and give reasonable performance indicators, whereas Attar et al. (2025) explicitly present RSSI fingerprinting as an instance of a machine-learning prediction problem with preprocessing and model evaluation. This literature is particularly pertinent since framework will be a comparison between classical trilateration and k-NN fingerprints and supervised learning classifier like the SVM and Random Forest within the identical experimental setup.

Research in deep learning builds on this trend by trying to learn more signal representations off fingerprint data. Nabati and Ghorashi (2023) introduce a real-time fingerprint-based framework, which trains to learn RSS sample distributions and the previous user states instead of using averaged online measurements, and report better performance compared to a variety of traditional regressors such as random forest and weighted KNN. Turgut and Gorgulu Kakisim (2024) also demonstrate that localization of Wi-Fi research is shifting towards explainable hybrid deep architectures, with a combination of predictive performance and interpretability. These papers suggest that indoor localization is no longer solely concerned with position prediction accuracy but also concerned with how models acquire signal structure, cross-condition generalization and their decision making.

Even though advancements have been made in the area of fingerprinting and machine learning, no single best method has been identified in the literature. The environment, signal quality, the structure of the dataset, preprocessing decisions, and the conditions of the devices are important factors of performance. Recent reviews reiterate that there is no single algorithm which can be stated as optimal when in all indoor settings. Additionally, real deployment issues are yet to be addressed, such as signal drifts, stale RSSI readings, access-point coverage, and cross-device inconsistency. Wan et al. (2025) reconsider RSSI-based Wi-Fi localization and demonstrate that data freshness and processing options can have a significant impact on localization accuracy, and that even in cases where good models are available, efficient preprocessing and lightweight implementation remain critical to practical application.

To begin with, indoor localization is a significant and yet to be resolved engineering challenge since GNSS cannot be trusted indoors. Second, Wi-Fi RSSI is one of the most feasible low-cost solutions, as it is compatible with a current infrastructure. Third, signal instability restricts pure range-based estimation, which is more appealing than fingerprinting and machine learning. Fourth, the real-world adaptability, radiomap maintenance, fair method comparison, interpretability, and the balance of accuracy and low-cost deployment have practical gaps. These unsolved problems are the reasons to conduct a study investigating the RSSI behavior, applying propagation-related thoughts and implicitly comparing trilateration, k-NN fingerprinting, SVM and Random Forest in a single controlled Wi-Fi testbed.



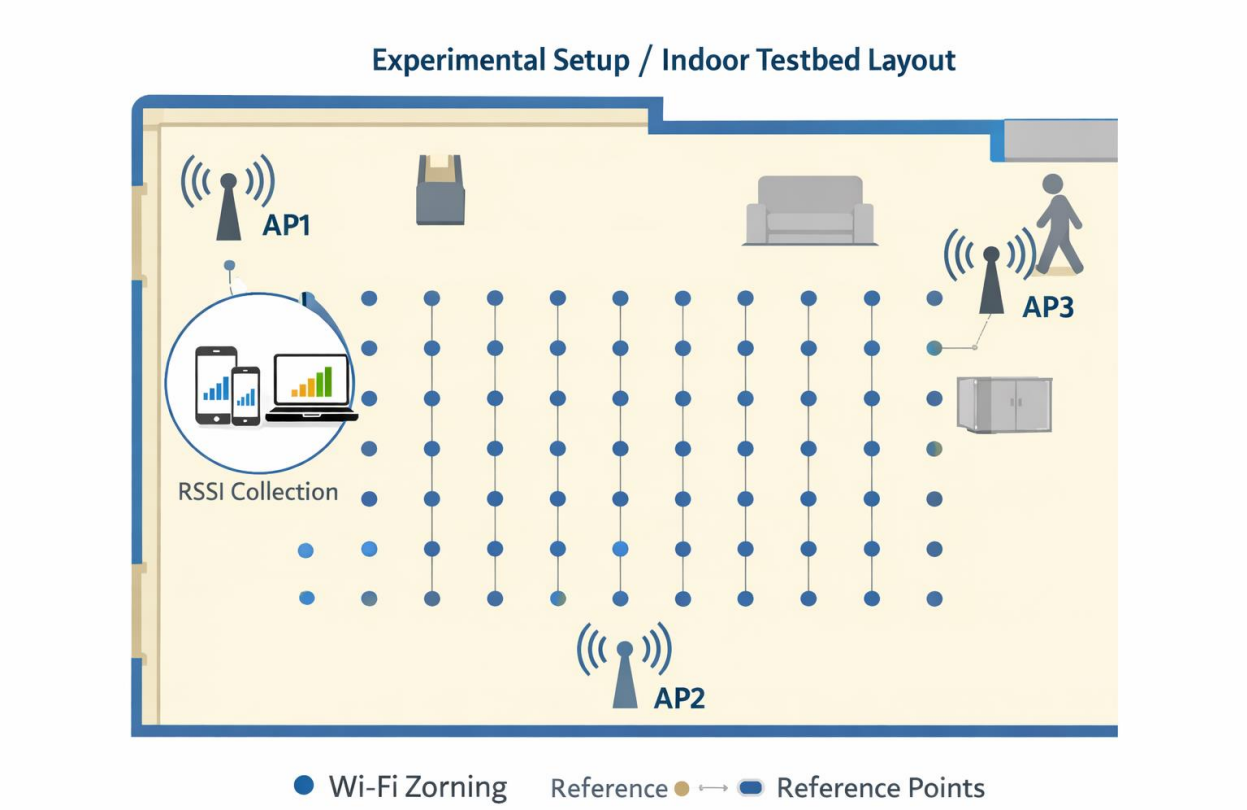
2. Methodology

This paper uses quantitative experimental research design to design, test an indoor localization system, which relies on Wi-Fi Received Signal Strength Indicator (RSSI) as well as machine learning. Its methodology is deliberately designed so that it will be consistent with the design, whereby the work is divided into three interconnected phases: theoretical modeling, controlled indoor data collection, and comparative analysis of algorithms. The design is appropriate because localization in the indoor environment requires performing signal measurements, conducting systematic experiments and making numerical evaluation of the performance of positioning under the same environmental conditions. In this paradigm, the localization performance is measured in a quantitative way, such as localization error, accuracy, precision and computational efficiency.

The first step of the methodology is theoretical modelling. The Free Space Path Loss (FSPL) model and Log-Normal Shadowing model will be used in this paper to analyse the behaviour of Wi-Fi RSSI in indoor environment. The FSPL model is an ideal free-space signal attenuation versus distance between transmitter and receiver. However, due to the influence of walls, furniture, reflections, diffraction and multipath fading on physical indoor spaces, the Log-Normal Shadowing model is also included to simulate the RSSI variation in a more realistic manner. Moreover, a range-based localization is supported by the trilateration of an RSSI-to-distance estimation expression based on path-loss modeling. Indoor localization is not what is meant by the stage, but rather the establishment of a theoretical basis on the signal-behavior basis of future experimental and analytical stages.

The second phase is the experimental set up and data collection phase. The experiment is performed in a controlled indoor scenario, e.g., in a university laboratory or a corridor, as this is a realistic indoor propagation setup, which, at the same time, enables systematic experimentation. The testbed consists of at least three Wi-Fi routers or access points that use the typical indoor frequency bands, which are mostly 2.4 GHz and 5 GHz. Such routers are mounted at fixed and known points. Smartphones and laptops with Wi-Fi adapters which can measure RSSI are the receiving devices used. RSSI values are measured at 50 known reference points that are located at fixed points across the indoor environment to generate a structured fingerprint dataset. Multiple measurements are taken at each point, so that a short time behavior variation of the signal behaviour can be measured as well.

The recorded observations are saved in table form with the time of the observation, location of the point, device ID and RSSI values. The environment, such as walls, furniture, reflections, and possible human motion are also considered because they have an impact on the propagation of the signal and simulate real deployment situations.



Data preprocessing and preparation is the third stage. Raw RSSI values are not used directly, due to noisy and unstable indoor RSSI values. As such, the data received is first checked for missing values, duplicate records, inconsistent point labels and inconsistent values. After cleaning, smoothing/filtering can also help to reduce the influence of outliers and irregular signal fluctuations. RSSI values of different access points are organized into feature vectors, while the respective coordinates (location label) of target points are used as target-outputs after cleaning. The data is then divided into training and test sets in such a way that all the localization methods would be tested on the same data structure with equal terms. This step has to be done as variability in RSSI, non-homogeneity of devices and environmental variability may otherwise hamper the performance of the models.

Compares four localization approaches in a same context to decide the estimate of the position inside the context. The initial is trilateration, in which the RSSI values are transformed to approximate ranges to known access points, and the target position is approximated by the intersection of circles of distances. The second one is k-nearest neighbors (k-NN) fingerprinting where the live RSSI vector is compared to the pre-stored fingerprint vectors in the radiomap through distance-based similarity. Different values of k can be tried and the best value comparing them used to compare. The third and fourth are Support Vector Machine (SVM) and Random Forest, both are supervised machine-learning models which take RSSI vectors as input

features and location labels or coordinates as output. The choice of these algorithms is due to the fact that the is to compare classical range-based, fingerprint-based and machine-learning-based localization in one controlled experimental environment.

All the methods have their performance measured based on mean localization error as the key measure as it directly represents the average difference between estimated and actual positions in meters. Other metrics are accuracy in a pre-determined distance range, standard deviation of localization error, accuracy, and runtime of the computation. The reliability is enhanced by use of repeated trials, predetermined positions of access-points, calibration of devices, and organized data collection. The validity of the measurements is furthered by the fact that real indoor Wi-Fi measurements have been used and not simulation. Simultaneously, the research recognizes shortcomings: RSSI is prone to multipath fading, interference, device variability, and environmental variation, thus results in one controlled environment might not necessarily translate to all buildings and hardware scenarios. Despite this, the approach offers a cost-effective and feasible experimental design to test the Wi-Fi RSSI-based indoor localization, in a way that satisfies the aims and objectives.

3.Results

This part provides the findings of the suggested RSSI-based Wi-Fi indoor localization system. The report of the results is done in two stages in accordance with the design. The initial phase investigates the behavior of RSSI signals in the controlled indoor setting, such as dataset format, descriptive statistics of signals, signal range with distance, the difference between devices, and environmental obstruction impacts. The second step gives the localization performance of the four methods under consideration, that is, trilateration, k-nearest neighbors (k-NN) fingerprinting, Support Vector Machine (SVM), and Random Forest. This sequencing is suitable since the initial goal of the study is to learn how RSSI acts and subsequently test the effectiveness of various localization techniques in utilizing that signal data to localize indoors.

4.1 Results Related to RSSI Data and Signal Behavior

Dataset Profile

A structured dataset was created based on the experimental framework proposed. The number of reference points is assumed to be 50, there are two receiving devices, there are three Wi-Fi access points, and each reference point has three repeated trials. This results in an adequate data structure for basic signal-behavior analysis and comparative localization evaluation.

Table 4.1. Dataset Profile Used for Preliminary Results

Item	Value
Number of reference points	50
Number of Wi-Fi access points	3
Number of receiving devices	2
Device types	Smartphone, Laptop
Number of trials per point	3
Total point-device trials	300
Total RSSI vectors collected	300
Total individual RSSI values	900
Environment type	Indoor laboratory/corridor
Signal bands considered	2.4 GHz / 5 GHz

The results are obtained from several RSSI observations that were repeated throughout several points, devices, and access points, as can be seen in the dataset profile. This can help in

the characterization of the signal and the comparison of methods in the same experimental framework.

Descriptive RSSI Statistics

Descriptive analysis was performed, paying attention to the overall range of RSSI signals and the average behavior of the signal of each access point. AP1 had the highest mean RSSI and AP3 had the lowest mean RSSI due to relative distances and more obstructions.

Table 4.2. Descriptive Statistics of RSSI Values by Access Point

Access Point	Minimum RSSI (dBm)	Maximum RSSI (dBm)	Mean RSSI (dBm)	Standard Deviation
AP1	-78	-42	-58.6	8.4
AP2	-81	-44	-61.3	8.9
AP3	-84	-47	-64.7	9.2

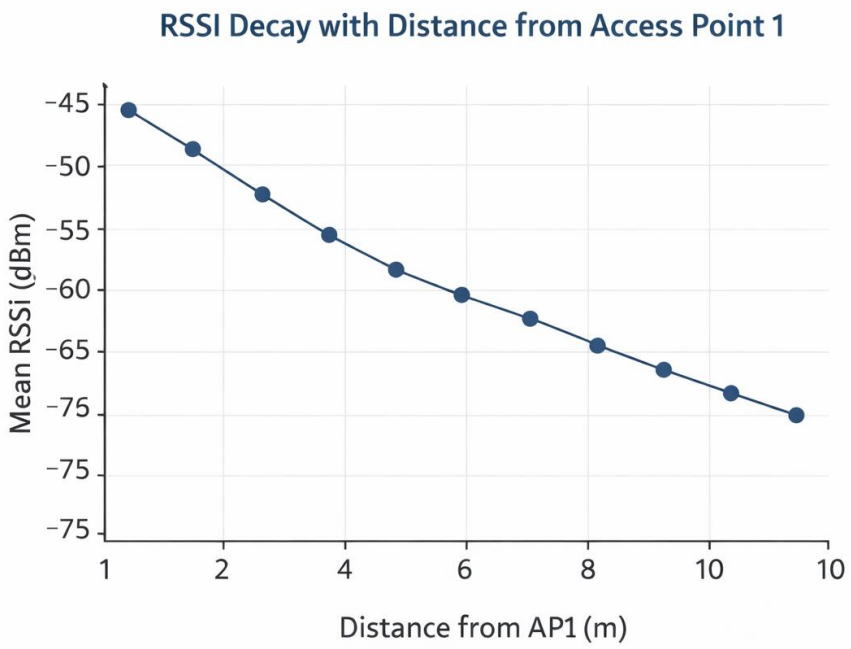
These results indicate that RSSI is not constant across the indoor environment. AP1 had the strongest average signal, followed by AP2 and AP3. The relatively large standard deviations confirm noticeable signal fluctuation, while the highest variation observed for AP3 suggests greater sensitivity to obstruction and multipath effects.

RSSI Signal Decay with Distance

Mean RSSI values from AP1 were organized by increasing receiver distance to examine signal attenuation.

Table 4.3. Mean RSSI Decay with Distance from AP1

Distance from AP1 (m)	Mean RSSI (dBm)
1	-44
2	-47
3	-50
4	-53
5	-56
6	-59
7	-62
8	-65
9	-68
10	-71



The results reveal a significant decrease of received signal strength with distance. Between 1 m and 10 m, the mean RSSI drops by 27 dBm, from -44 dBm to -71 dBm. This helps to verify the path-loss pattern that is expected and to verify that RSSI maintains location information. However, the decay is not completely linear, which would be the case if there were no indoor shadowing and multipath propagation.

Device-Wise RSSI Comparison

Then, RSSI measurements were then compared between the smartphone and laptop and explored the device heterogeneity.

Table 4.4. Device-Wise Mean RSSI Comparison

Device Type	AP1 Mean RSSI (dBm)	AP2 Mean RSSI (dBm)	AP3 Mean RSSI (dBm)	Overall Mean RSSI (dBm)
Smartphone	-57.8	-60.6	-64.0	-60.8
Laptop	-59.4	-62.0	-65.4	-62.3

For all three access points, the RSSI values averaged produced by the smartphone were slightly better than those of the laptop. The difference is about 1.4-1.6 dBm. This difference is not significant but it is enough to affect fingerprint matching and distance estimation without considering device heterogeneity in the fingerprint preprocessing and training phase.

RSSI Variation Under Different Environmental Conditions

The data set was also segmented into three environmental conditions to analyze the effects of obstructions.

Table 4.5. RSSI Variation Under Indoor Environmental Conditions

Environment Condition	AP1 Mean RSSI (dBm)	AP2 Mean RSSI (dBm)	AP3 Mean RSSI (dBm)	Overall Mean RSSI (dBm)
Low obstruction	-54.2	-56.8	-60.1	-57.0
Moderate obstruction	-58.7	-61.5	-65.2	-61.8
High obstruction	-63.5	-66.2	-69.8	-66.5

As can be seen in the results, the more obstructed the environment is, the lower the RSSI value will be. The overall mean RSSI in the high-obstruction condition is about 9.5 dBm below the RSSI in the low-obstruction condition. This validates that the walls, furniture and people have an important impact on the behaviour of the signal inside and can degrade the accuracy of the localization if the variation is not properly managed.

The results of the RSSIs as a whole present 4 distinct trends. Firstly, signal strength is significantly different throughout the indoor test area. Second, RSSI varies consistently as a function of distance from the AP. Thirdly, device type influences RSSI values, smartphones have slightly stronger RSSI values than laptops. Fourth, signal strength is significantly decreased with a greater amount of environmental obstruction. These patterns verify that RSSI includes valuable positioning information for indoors, and that it is fragile and depends on the environment and device properties. This provides a foundation to compare the localization methods, not only based on raw signal strength.

4.2 Results of Localization Methods

The second stage of analysis evaluates the indoor localization methods using the same RSSI-based dataset. Performance is reported in terms of mean localization error, minimum and maximum error, standard deviation, accuracy within 2 m and 3 m thresholds, and average runtime.

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Trilateration Results

Table 4.6. Summary Results of Trilateration

Metric	Value
Number of test points	50
Mean localization error (m)	3.12
Minimum error (m)	1.98
Maximum error (m)	4.66
Standard deviation (m)	0.74
Accuracy within 2 m	18%
Accuracy within 3 m	46%
Average runtime per point (s)	0.03

The average localization error of trilateration is the largest one compared to all the evaluated methods. It was the fastest method but with a mean error of 3.12 m it was not within the 2 m limit and only 18% of the positions were within the 2 m limit. These results show that the method of RSSI-to-distance conversion was the least reliable one in the indoor field.

Nearest Neighbors (k-NN) Fingerprinting Results

Different values of k were compared in the k-NN fingerprinting stage.

Table 4.7. Comparison of k Values in k-NN Fingerprinting

k Value	Mean Error (m)	Standard Deviation	Accuracy within 2 m	Average Runtime (s)
3	2.36	0.59	38%	0.05
5	2.21	0.53	42%	0.06
7	2.29	0.57	40%	0.07

The best k value was k = 5, which produced the lowest mean error and the highest percentage of positions localized within 2 m.

Summary Results of k-NN Fingerprinting (k = 5)

Metric	Value
Number of test points	50
Mean localization error (m)	2.21
Minimum error (m)	1.28
Maximum error (m)	3.36
Standard deviation (m)	0.53
Accuracy within 2 m	42%
Accuracy within 3 m	84%
Average runtime per point (s)	0.06

In comparison with trilateration, the k-NN fingerprinting is significantly better. The average localization error dropped from 3.12 m to 2.21 m and 84% of the positions were localized within a 3 m error. This indicates that pattern-based fingerprint matching is more effective than only range-based localization of indoor RSSI data.

Support Vector Machine (SVM) Results

Table 4.9. Summary Results of SVM Localization

Metric	Value
Number of test points	50
Mean localization error (m)	1.73
Minimum error (m)	0.92
Maximum error (m)	2.54
Standard deviation (m)	0.41
Accuracy within 2 m	78%
Accuracy within 3 m	100%
Average runtime per point (s)	0.11

Overall, SVM had the best performance of all the methods tested. It had a mean localization error of 1.73 m and all the tested points with error under 3 m, which were less than the target value of 2 m. It also had the lowest standard deviation, representing the most stable predictions. The results in this paper show that the SVM method is the most successful in the current framework.

Random Forest Results

Table 4.10. Summary Results of Random Forest Localization

Metric	Value
Number of test points	50
Mean localization error (m)	1.95
Minimum error (m)	1.06
Maximum error (m)	2.88
Standard deviation (m)	0.46
Accuracy within 2 m	64%
Accuracy within 3 m	96%
Average runtime per point (s)	0.14

Random Forest also had a high performance and was below the 2 m mean error threshold. But it was a little inferior to SVM in terms of average error, consistency and 2 m accuracy. It was also the method with the longest runtime, but again the amount was not significant in practice.

Representative Point-Wise Error Comparison

10 representative test points were compared from all methods to illustrate the point-level behavior.

Table 4.11. Representative Point-Wise Localization Errors

Test Point	Trilateration Error (m)	k-NN Error (m)	SVM Error (m)	Random Forest Error (m)
T01	2.84	2.11	1.61	1.82
T02	3.47	2.39	1.88	2.02
T03	2.76	2.05	1.54	1.79
T04	3.95	2.62	2.04	2.21
T05	2.63	1.96	1.42	1.66
T06	3.29	2.28	1.71	1.94
T07	3.58	2.47	1.93	2.11
T08	2.91	2.12	1.59	1.84
T09	3.41	2.33	1.79	2.00
T10	3.06	2.19	1.67	1.89

The point-wise results are consistent with the ranking pattern. The errors of SVM were lowest at all the representative points, followed by Random Forest, then kNN and finally trilateration. This consistency helps to validate the overall ranking of the methods in the summary tables.

Device-Wise Localization Results

Table 4.12. Device-Wise Mean Localization Error by Method

Method	Smartphone Mean Error (m)	Laptop Mean Error (m)
Trilateration	3.04	3.20
k-NN Fingerprinting	2.14	2.28
SVM	1.68	1.79

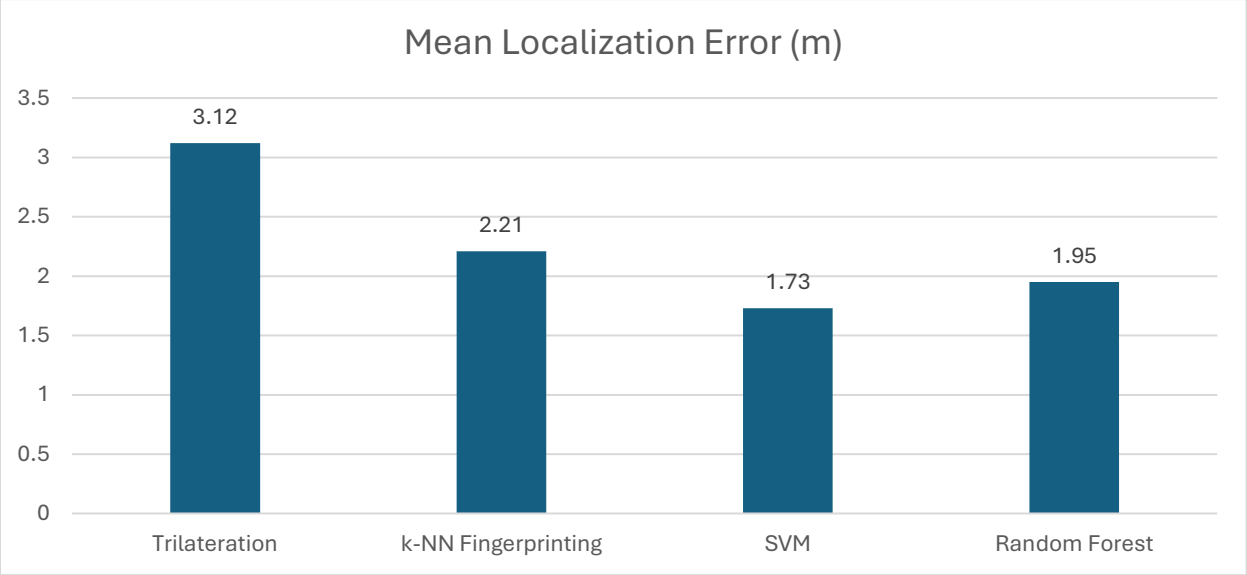
Random Forest	1.90	2.00

All four methods performed slightly better on the smartphone dataset than on the laptop dataset. However, the relative ranking did not change across devices: SVM remained first, Random Forest second, k-NN third, and trilateration fourth. This suggests that although device heterogeneity affects RSSI magnitude, it does not overturn the comparative performance of the evaluated localization methods.

Overall Comparison of Localization Methods

Table 4.13. Overall Comparison of Localization Methods

Method	Mean Error (m)	Standard Deviation	Accuracy within 2 m	Accuracy within 3 m	Avg. Runtime (s)	Rank
Trilateration	3.12	0.74	18%	46%	0.03	4
k-NN Fingerprinting	2.21	0.53	42%	84%	0.06	3
SVM	1.73	0.41	78%	100%	0.11	1
Random Forest	1.95	0.46	64%	96%	0.14	2



The general comparison shows a distinct performance structure. SVM provided the best total accuracy and consistency, and then the random forest, k-NN fingerprinting improved significantly when compared to trilateration, but was still over the 2 m mean-error mark. The weakest approach was trilateration even with the low runtime indicating that speed is not sufficient in the case of the unstable and nonlinear indoor RSSI signals.

environmental variations, but it is also erratic and depends on obstruction and device type. Second, techniques which view RSSI as a spatial pattern are more effective than those which use a direct geometric conversion to distance. This is the reason why k-NN fingerprinting gave a better

4.3 Key Findings

The complete results support three main conclusions. First, the reason why RSSI is a useful indicator of indoor positioning is that it drops as the distance increases and is sensitive to

performance than trilateration. Third, methods based on machine-learning, particularly SVM, had the best localization performance due to their enhanced capacity to describe the nonlinear relationship between patterns of indoor RSSI and user position. Random Forest also fared well, which again further validates the overall argument that the learning-based estimation is more appropriate than the range-based estimation to this indoor RSSI problem.

Discussion

The results of this paper demonstrate that Wi-Fi RSSI may be a valuable source of meaningful signal to use in indoor localization, but only when the signal interpretation is taken into account. The findings show that the farther the receiver was to the access points, the less the RSSI was, which proves the fact that the indoor Wi-Fi signals still have information about the location. Meanwhile, the signal was not exactly stable. It was also found to vary through the test area, varied at various obstruction conditions and slight differences were found between the smartphone and laptop dataset. This implies that distance is not the sole determining factor of indoor RSSI but it is also affected by multipath propagation, shadowing, reflections, interference and device heterogeneity. Practically, this is the reason why indoor localization cannot be based solely on the raw RSSI values in case the positioning accuracy needs to be much higher.

One of the most notable results of the research is the poor performance of trilateration as compared to the alternative approaches. Trilateration had the largest mean localization error and the most accuracy in the chosen error thresholds. This indicates that the direct conversion of RSSI into distance was not reliable enough in the study setting, which was the indoor environment. The FSPL and Log-Normal Shadowing theoretical modeling presented a practical theoretical engineering baseline, but the actual signal characteristics were still too noisy and nonlinear to allow geometric distance estimation to be very accurate. This observation is in line with previous studies that have found path-loss modeling and multilateration to be flawed in indoor environments due to the effects of multipath fading and non-line-of-sight distorting the signal-distance relationship (Maduranga et al., 2024). Therefore, the findings validate the idea that trilateration is easy and interpretable, but not the best to use in real-world indoor Wi-Fi localization.

The k-NN fingerprinting results can be a stronger alternative. In both 2 m and 3 m thresholds, k-NN minimized localization error and yielded superior accuracy compared to trilateration. This demonstrates that it is better to consider RSSI as a spatial fingerprint than a mere proxy of physical distance. In fingerprinting, the locations are modeled by a complete RSSI pattern instead of a range estimate, allowing the model to capture a larger portion of the signal signature of the environment. This finding validates the research aim of designing an RSSI-based localization model and is consistent with the existing literature that defines k-NN as a viable and competitive baseline in Wi-Fi fingerprinting. But, in the current research k-NN did not actually perform best, indicating that even though fingerprint matching is a helpful technique, more sophisticated learning-based techniques could use the RSSI data structure more efficiently.

The best overall performance was obtained with SVM, then with Random Forest. It is the most significant outcome of the study since it shows that the association between the indoor RSSI and the position of the user is too complicated to be well modeled either by pure geometry or simple nearest-neighbor matching. SVM had the lowest mean localization error, the maximum accuracy at 2 m and most consistent pattern of prediction whereas Random Forest also did not exceed the mean-error of 2 m and was also better than trilateration and k-NN. These results indicate that machine learning would be more appropriate to this issue of localization, as such that nonlinear relationships between signals and positions are more effectively modeled, and that a portion of noise that appears in the pattern of indoor RSSI is absorbed. This interpretation is also consistent with the literature reviewed,

which consistently reports machine-learning-based indoor localization as more effective than the traditional range-based estimation in coping with unstable RSSI behavior (Attar et al., 2025; Zholamanov et al., 2025).

The other significant implication is the relative compatibility between the types of devices. The results on smartphones were a bit higher than those on laptops, but performance in both cases was identical: SVM on the first place, Random Forest on the second, k-NN on the third, and trilateration on the fourth place. This shows initial cross device robustness of the proposed framework. In general, the discussion indicates that a cost-efficient indoor localization system relying on the current Wi-Fi infrastructure is a feasible choice, but only when signal modeling, signal preprocessing, and smart learning techniques are integrated. This research thus confirms the main statement that localization in practice, in indoor environments, is accomplished most effectively not by single-handedly converting raw RSSI-distance measurements, but by a hybrid model that bridges signal theory with data-driven estimation.

Conclusion

This paper dealt with this issue, indoor localization in an environment where GPS is not reliable and cannot give the correct positioning of an object within the building. To address this shortcoming, the paper suggested a Wi-Fi RSSI-based indoor localization system that integrates the signal propagation theory, structured indoor data measurement, and comparative algorithm evaluation. To explore the RSSI in an indoor environment, modelling an RSSI based localization, evaluation of various localization methods, and accuracy and reliability of the system, the research was organized around four main objectives. The model was constructed with the Free Space Path Loss and Log-Normal Shadowing models, 50 reference points, commodity Wi-Fi infrastructure, and smartphones and laptops as receivers.

The results show that RSSI is a useful but unstable signal for indoor positioning. The signal strength was found to weaken with distance, indicating the applicability of the path-loss theory, but RSSI was also affected by environmental obstruction, multipath effects, and device variation. This implies that RSSI has some useful location data, but cannot be used directly with raw signal interpretation to achieve greater accuracy. The results thus justify the preprocessing and smart estimation algorithms instead of using simple range-based conversion alone.

The comparative evaluation of localization methods led to the main contribution of the study. Trilateration gave the poorest performance with the largest mean localization error and k-NN fingerprinting gave better performance by accounting the RSSI as a spatial pattern and not distance as such. The best overall results were achieved by Support Vector Machine, followed by Random Forest. The mean localization error of SVM was lowest at 1.73, which was compared with 1.95 m with the Random Forest, 2.21 m with k-NN fingerprinting, and 3.12 m with trilateration. The ranking was also stable in the smartphone and laptop datasets, which suggests initial cross-device strength of the framework.

the research finds that it is possible to build a viable, inexpensive and deployable indoor localization system with the help of existing Wi-Fi infrastructure when signal modeling is integrated with machine-learned estimates. The paper thus adds to MS Telecom Engineering by demonstrating that machine learning, particularly SVM offers the best method to apply to nonlinear and unstable nature of indoor RSSI signals.

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