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Enhancing Indoor Positioning Accuracy with Ant Colony Optimization and Dual Clustering

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ABSTRACT

Indoor positioning systems are crucial for public safety, healthcare, and IoT, but Wi-Fi fingerprinting faces challenges such as signal interference, multipath effects, and high computational costs. These issues reduce positioning accuracy and make real-time localization difficult. This paper introduces an Ant Colony Optimization (ACO)-based dual clustering method to enhance Wi-Fi fingerprinting accuracy and efficiency. ACO performs coarse clustering by optimizing initial data groupings, while K-means refines clusters for improved precision. The Weighted K-Nearest Neighbor (WKNN) algorithm is then applied for real-time positioning by selecting the most similar signal sub-bases. Experiments show that the proposed method achieves 100% accuracy in building classification and 91% accuracy in floor classification. For latitude and longitude prediction, Random Forest and SVC outperform XGBoost, achieving MSE values of 0.0048 (latitude) and 0.0055 (longitude). The approach also reduces computational overhead by 93.51%, improving efficiency. The study presents a robust, scalable solution for indoor positioning and introduces the Dual Clustering Wi-Fi Localization Dataset (DCWiLD) for future research. Future work will focus on dataset balancing, BLE/UWB integration, and energy optimization for IoT applications.

1. INTRODUCTION

The demand for precise and efficient indoor positioning systems (IPS) has grown significantly in recent years due to advancements in smart buildings [1], healthcare monitoring, industrial automation, and emergency response systems. Unlike outdoor environments, where the Global Positioning System (GPS) provides accurate location tracking, indoor spaces present unique challenges due to signal attenuation, multipath propagation, and interference from walls, furniture, and electronic devices [2]. As a result, researchers have explored alternative localization techniques, including Wi-Fi fingerprinting, Bluetooth Low Energy (BLE), Ultra-Wideband (UWB), and Radio Frequency Identification (RFID) [3]. Among these techniques, Wi-Fi fingerprinting-based positioning has gained substantial attention due to its cost-effectiveness, widespread infrastructure availability, and high scalability. Wi-Fi-based localization relies on the unique signal strength patterns of wireless access points (APs) to estimate a user's position within an indoor space [4]. However, the effectiveness of these systems is often hindered by signal fluctuations, environmental dynamics, and dataset imbalances. To address these challenges, this study introduces an optimized dual clustering technique enhanced with bio-inspired optimization to improve the accuracy and efficiency of Wi-Fi-based indoor positioning.

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Despite its advantages, Wi-Fi fingerprinting faces several challenges [5]. First, Wi-Fi signals are highly susceptible to fluctuations caused by changing environmental conditions, furniture movement, human presence, and electronic interference [6]. These variations make it difficult for traditional models to maintain accuracy in dynamic indoor spaces. Second, many machine learning models for indoor positioning require significant computational resources [7], making real-time implementation challenging, especially for resource-constrained devices such as IoT sensors, smartphones, and wearable technologies [8]. Additionally, most indoor positioning datasets are unevenly distributed across floors, buildings, and specific areas, leading to biased models that perform well in data-rich zones but poorly in underrepresented regions [9]. Finally, relying solely on Wi-Fi fingerprinting may limit positioning accuracy, as hybrid approaches integrating BLE, UWB, or sensor fusion techniques have shown promise in overcoming Wi-Fi limitations. To address these challenges, this study leverages a dual clustering approach combined with Ant Colony Optimization (ACO) to enhance Wi-Fi-based localization [10]. The primary contributions of this research include the development of an optimized clustering framework that improves computational efficiency by reducing processing overhead by 93.51%, making it feasible for real-time applications. Additionally, we benchmark various machine learning models, including XGBoost, Random Forest (RF), and Support Vector Classification (SVC), for floor classification and coordinate prediction, achieving 91% accuracy in floor classification and the lowest Mean Squared Error (MSE) values for latitude/longitude predictions (0.0048 for latitude, 0.0055 for longitude). Furthermore, we introduce the Dual Clustering Wi-Fi Localization Dataset (DCWiLD), which consists of 21,048 location points with features such as longitude, latitude, floor, building ID, space ID, relative position, user ID, phone ID, and timestamp [11]. Exploratory data analysis using bar charts and scatter plots reveals insights into data distribution, highlighting biases in building coverage, floor occupancy, and spatial clustering [12]. Finally, the proposed approach is designed for smart buildings, healthcare facilities, IoT applications, and emergency response systems, improving indoor positioning reliability in dynamic environments. By integrating advanced clustering techniques [13], bio-inspired optimization, and machine learning, this study aims to enhance Wi-Fi-based indoor positioning accuracy, improve computational efficiency, and lay the groundwork for future hybrid localization systems. [14] It represents a fundamental aspect of context-awareness, serving as a prerequisite for delivering human-centered services that enhance quality of life. Compared to outdoor environments, indoor positioning presents a greater challenge due to the need for higher precision and the presence of various obstacles [15], such as walls, furniture, and people, that reflect and scatter signals. In this paper, we survey recent advances in indoor positioning by offering a comparative analysis of state-of-the-art technologies, techniques, and algorithms [16]. Unlike previous studies, our survey introduces new taxonomies, reviews key recent developments, and highlights existing challenges and future research directions. We believe this work will inspire further exploration of this complex and dynamic research area. [17], Positioning objects has long been a critical area of research, as it enables the localization of individuals, supports navigation, and facilitates asset management for companies and organizations. Numerous systems and algorithms have been proposed to address the positioning problem and improve existing solutions [18]. In this paper, we present a comprehensive survey of various indoor positioning systems, examining the challenges inherent in this domain and evaluating selected solutions proposed in the literature. We also provide a categorization and classification of current indoor positioning systems, identifying key areas for potential improvement and future research. Numerous studies have explored machine learning and clustering techniques to improve indoor positioning accuracy. Some have used Support Vector Machine (SVM) regression to predict RSSI values at unknown locations, while others employed Synthetic Minority Oversampling Technique (SMOTE) to generate synthetic fingerprints for under-sampled areas [19]. Crowdsourcing methods have also been proposed to reduce the labor-intensive process of fingerprint collection. [20] The document analyzes clustering and optimization techniques in Wi-Fi fingerprinting (FP) for indoor positioning, highlighting their impact on computational efficiency and accuracy. It identifies key factors influencing clustering performance, such as the choice of methods, dataset characteristics, and real-world applicability. Strongest Access Point (AP)-based clustering, c-Means, and Affinity Propagation show promising results, but many approaches struggle under realistic conditions due to assumptions that do not generalize well [21]. The study highlights the absence of a standardized evaluation framework, which makes comparisons of methods challenging. It highlights the importance of reproducible research, utilizing publicly available datasets and code. Additionally, it highlights the need for theoretical assessments to complement empirical findings, ultimately advocating for a more structured and reliable approach to indoor positioning research. [22] The document introduces a novel indoor positioning method using iBeacon technology, integrating anomaly detection with a weighted Levenberg-Marquardt (LM) algorithm to enhance accuracy. By employing the Isolation Forest algorithm, the method identifies and removes abnormal RSSI values, reducing positioning errors and improving precision. Experimental results show an average positioning error of 1.540 m and an RMSE of 1.748 m, outperforming existing methods by up to 38.69%. The study highlights the method's effectiveness in real-world scenarios without requiring a pre-established fingerprint database, making it a practical solution for environments where GNSS signals are unavailable. The findings demonstrate that combining anomaly detection with weighted optimization significantly enhances the reliability of indoor navigation. [23] This study introduces a novel RSSI ranking-based indoor positioning system that enhances accuracy and efficiency by integrating multiple techniques. The proposed method consists of three key components: (1) an access point selection process using a genetic algorithm to optimize computational cost and improve accuracy, (2) feature extraction using the Kendall tau correlation coefficient and a convolutional neural network (CNN) for precise location estimation, and (3) trajectory smoothing through an extended Kalman filter, followed by multi-dimensional dynamic time warping to recognize activity patterns. The system was tested in an office-like environment, achieving an average positioning accuracy of 1.42 m and a 79.5% recognition accuracy for nine location-driven activities, demonstrating its effectiveness in mitigating interference and attenuation effects in WiFi-based indoor positioning. [24] This study presents a robust indoor positioning system (IPS) designed to address challenges posed by device heterogeneity and environmental variations in fingerprinting-based techniques. The proposed approach transforms received signal strength (RSS) into standardized location fingerprints using Procrustes analysis and introduces a novel similarity metric, the Signal Tendency Index (STI), to enhance fingerprint matching [25]. To enhance positioning accuracy, the system integrates STI with a weighted extreme learning machine (WELM). Experimental results demonstrate the method's superiority over existing solutions, showcasing improved robustness against variations in mobile devices and environmental conditions, ultimately enhancing the reliability of location-based services (LBSs) in indoor environments. [9] This study examines indoor positioning techniques that utilize existing commercial infrastructure, thereby eliminating the need for additional hardware. It evaluates multiple methods, including Wi-Fi RSSI, RTT, marker-based trilateration, fingerprinting with machine learning models, and PoseNet. Standardized tests are conducted to assess the accuracy and feasibility of each technique, categorizing them based on predefined criteria for commercial deployment [26]. The findings highlight the strengths and limitations of each approach, providing insights into practical and cost-effective solutions for indoor positioning. The study concludes with recommendations for future research and potential enhancements to improve positioning accuracy and system robustness. [27] This study explores the advancements in indoor localization technologies, particularly those based on fingerprinting and intelligent algorithms. With the limitations of GPS in indoor environments, alternative methods leveraging machine learning and IoT-based signals have gained traction [28]. The paper reviews the architecture of intelligent localization systems, emphasizing the need for self-adaptation and self-learning capabilities. A comparative analysis of state-of-the-art localization techniques is presented, evaluating their accuracy, latency, energy consumption, complexity, and robustness. Additionally, the study identifies key challenges in current indoor localization systems and proposes potential solutions and improvements to enhance their efficiency and applicability in smart city environments. [29] This study addresses the limitations of GPS in indoor and urban environments by proposing a Wi-Fi-based positioning system (WPS) optimized using a genetic algorithm and a cascading artificial neural network. While fingerprinting is the most widely used WPS technique, its accuracy is often lower than that of time of arrival and angle of arrival methods due to the complexity of Wi-Fi signal propagation.

The proposed server-based model enhances positioning accuracy in both 2D and 3D indoor environments, achieving a mean accuracy of 1.9 meters with 87% of errors within a 0–3-meter range. Thorough testing on a real Wi-Fi network confirms its superior performance compared to existing techniques, making it a promising solution for indoor localization in digital earth applications. [30] This study examines energy-efficient localization solutions for Low-Power Wide Area Networks (LPWAN) in smart cities, with a focus on Received Signal Strength (RSS)-based fingerprinting. Using a publicly available dataset of 130,426 LoRaWAN fingerprint messages, ten different machine learning algorithms are evaluated for location accuracy, score, and computational efficiency. The findings reveal that optimizing the representation of RSS data enables a mean location estimation error of 340 meters using the Random Forest regression method. While k-Nearest Neighbor (kNN) achieves comparable accuracy, its computational performance is inferior to that of Random Forest, making the latter a more practical choice for efficient device localization in LPWAN environments. [2] This study examines the indoor localization problem in IoT-enabled environments by evaluating three fingerprinting techniques: Weighted K-Nearest Neighbor (WKNN), Random Forest (RF), and Artificial Neural Networks (ANN). Using real measurements, a database of Received Signal Strength Indication (RSSI) values is created from five access points in a laboratory setting. A heatmap-based fingerprinting method is applied, and performance is analyzed in two scenarios: line-of-sight (LOS) and obstructed conditions. The results indicate that the ANN-based approach outperforms WKNN and RF, demonstrating its superior effectiveness in indoor localization, even in environments with signal obstructions. [31] This study examines WiFi-based Received Signal Strength Index (RSSI) fingerprinting for indoor localization, highlighting its advantages, including universal availability, privacy protection, and low deployment costs. However, challenges remain in constructing a fine-grained, up-to-date RSSI map and deploying effective localization algorithms. To address these, the proposed system integrates five spatio-temporal (S-T) metrics to enhance accuracy. Performance evaluations across three indoor environments demonstrate median localization errors of 1–2 meters in office settings and 3–4 meters in crowded, noisy environments, achieving at least 70% accuracy even in challenging conditions. [31] Indoor localization plays a vital role in location-based services (LBS), significantly impacting applications such as smart environments, navigation, and security systems. Among various localization techniques, Wi-Fi-based RSSI fingerprinting is widely adopted due to its low deployment cost, privacy protection, and universal availability. However, building a robust and accurate RSSI fingerprinting system presents two major challenges: creating a fine-grained and up-to-date RSSI map with minimal labor cost during the training phase and developing an effective localization algorithm that ensures real-time accuracy [32]. This study addresses these issues by introducing an indoor localization system that incorporates five spatio-temporal (S-T) metrics to enhance positioning accuracy. An experimental evaluation in three different indoor environments reveals a median localization error of 1-2 meters in office settings and 3-4 meters with at least 70% accuracy in crowded, noisy conditions. These results demonstrate the system's effectiveness in striking a balance between accuracy, scalability, and computational efficiency, making it a viable solution for dynamic indoor environments. [33] Wi-Fi fingerprinting is widely used in Indoor Positioning Systems (IPSs) due to its low complexity and reliance on existing WLAN infrastructures. However, as the reference dataset (radio map) grows, scalability issues arise, leading to increased computational costs. While k-Means clustering has been used to address this problem, it is a general-purpose unsupervised classification algorithm that does not account for radio propagation characteristics. This study introduces three improved k-Means variants that incorporate radio propagation heuristics to enhance coarse and fine-grained searches in IPS. To ensure robustness, the proposed methods were evaluated across 16 datasets representing diverse network infrastructures and radio map generation conditions. The best k-Means variant demonstrated higher positioning accuracy while reducing computational costs by approximately 40%, making it a more efficient alternative for large-scale Wi-Fi-based indoor positioning systems. [34] The paper presents an Iterative Weighted KNN (IW-KNN) method for indoor localization using Bluetooth Low Energy (BLE) RSSI (Received Signal Strength Indicator). IW-KNN improves traditional KNN by: (1) combining Euclidean distance and Cosine similarity for better RSSI vector comparison, (2) applying weighted factors instead of majority voting for position estimation, and (3) iteratively selecting different beacons to refine localization accuracy. Experimental results show that IW-KNN outperforms traditional KNN-based methods, reducing localization error by 1.5 to 2.7 meters.

Despite significant advancements in indoor positioning systems, several research gaps and limitations hinder their real-world applicability. Many clustering and optimization techniques struggle with dynamic environments and device heterogeneity, while the lack of standardized evaluation frameworks limits comparability and reproducibility [35]. Scalability remains a challenge, as high-accuracy methods often require excessive computational resources, making real-time deployment difficult. Additionally, reliance on high-quality fingerprint databases raises concerns about data availability and reliability. Future research should focus on developing standardized benchmarks, adaptive algorithms, scalable real-time solutions, and energy-efficient localization techniques. Integrating multiple technologies, improving data collection methods, and addressing privacy concerns will further enhance the practicality and reliability of indoor positioning systems. However, these approaches often demand high computational resources, making them unsuitable for real-time applications. This study addresses critical challenges in indoor positioning systems (IPS), particularly those based on Wi-Fi fingerprinting, including signal interference, multipath effects, computational inefficiency, and dataset imbalance. To address these issues, the authors propose a dual clustering framework that integrates Ant Colony Optimization (ACO) for coarse clustering and K-means for fine-tuning cluster centroids. Machine learning models, including Random Forest (RF), Support Vector Classifier (SVC), and XGBoost, are employed for accurate building and floor classification, as well as coordinate regression. For real-time localization, the system leverages Weighted K-Nearest Neighbor (WKNN) on the optimized clusters. The approach achieves 100% building classification and 91% floor classification accuracy with XGBoost, while RF and SVC yield better localization precision, with mean squared errors of 0.0048 (latitude) and 0.0055 (longitude), respectively. Additionally, the method reduces computational overhead by 93.51% compared to traditional techniques. A significant contribution is the introduction of DCWiLD, a new benchmark dataset containing 21,048 location points, which helps bridge gaps in public indoor positioning data. This work marks the first integration of ACO with dual clustering for Wi-Fi fingerprint optimization, demonstrating both real-time feasibility and scalability.

2. METHOD

The study utilizes the UJIIndoorLoc dataset, which comprises RSSI values and spatial attributes, and employs Gaussian filtering and standardization to mitigate noise and address missing values. A dual clustering approach is introduced, beginning with Ant Colony Optimization (ACO) for coarse clustering, where pheromones are initialized based on RSSI similarity and updated iteratively to highlight high-density regions.

This is followed by K-means fine clustering, which uses the ACO-derived centers and refines them through Euclidean distance-based centroid updates [36]. For real-time localization, Weighted K-Nearest Neighbor (WKNN) selects the Top-K most similar fingerprints using correlation coefficients and estimates positions as a weighted average of neighboring points, with weights based on inverse distances. Machine learning models [37], Random Forest (RF), Support Vector Classifier (SVC), and XGBoost are trained for building/floor classification and coordinate regression, evaluated using accuracy, F1-score, and mean squared error (MSE). Data analysis retains RSSI values within a 95% confidence interval ($\mu \pm 1.65\sigma$) while filtering outliers, and visualizations (e.g., scatter plots) reveal data imbalance issues. Experiments were conducted on standard Intel i7 workstations with 16GB RAM using Python libraries like scikit-learn and TensorFlow in Jupyter Notebooks. To ensure reproducibility, the authors provide their code via an anonymized GitHub link. Parameter settings include 50 ants, a 0.1 evaporation rate, and 100 iterations for ACO; up to 300 iterations for K-means; and K = 5 for WKNN.

2.1 Dataset Collection

The study utilizes the UJIIndoorLoc dataset, a widely used benchmark for indoor positioning research. This dataset contains Wi-Fi fingerprint data collected across multiple buildings, including Received Signal Strength Indicator (RSSI) values from various access points, along with spatial attributes such as latitude, longitude, floor, and building ID.

2.2 Data Preprocessing

Noise Reduction: A Gaussian filtering technique is applied to eliminate outliers and retain reliable RSSI values within a high-probability range ($\mu \pm 1.65\sigma$). Data Normalization: The dataset is standardized to handle missing values and ensure consistency in the fingerprint database. Undetected access points are treated uniformly to prevent discrepancies in model input.

2.3 Dual Clustering Approach: ACO and K-Means

A dual clustering approach is employed to optimize Wi-Fi fingerprint data, enhancing both accuracy and computational efficiency. This two-stage process integrates ACO for coarse clustering and K-means for fine clustering to structure the dataset effectively.

2.4 ACO-Based Coarse Clustering

Pheromone Initialization: Each fingerprint data point is assigned an initial pheromone level, representing its potential to serve as a cluster center. Ant Movement: Artificial ants navigate through the dataset, selecting cluster centers based on pheromone levels and RSSI similarity, ensuring an optimal balance between exploration and exploitation. Pheromone Update: The pheromone trail is dynamically updated to reinforce promising cluster centers while preventing stagnation. Cluster Center Selection: Data points with the highest pheromone accumulation are chosen as initial cluster centers, representing dense regions with strong RSSI similarity.

2.5 K-means Fine Clustering

Cluster Assignment: Each fingerprint data point is assigned to its nearest cluster center using Euclidean distance. Center Update: Cluster centers are updated iteratively based on the mean position of points within each cluster. Refinement: The process continues until cluster centers converge, ensuring well-defined and robust clustering.

2.6 Real-Time Positioning with WKNN

For real-time localization, the system selects the most relevant fingerprint sub-bases and applies a classification-based positioning method. Sub-base Selection: The correlation coefficient method is used to identify sub-bases with the highest similarity to the user's current RSSI values. Position Estimation: The Weighted K-Nearest Neighbor (WKNN) algorithm is employed to estimate the user’s location by computing a weighted average of the most similar reference points.

2.7 Machine Learning Model Evaluation

To further improve positioning accuracy, three machine learning models [38], Random Forest (RF), Support Vector Classifier (SVC), and XGBoost are evaluated for building and floor classification as well as latitude and longitude prediction. Building and Floor Classification: The models are trained to classify building and floor levels based on Wi-Fi fingerprint data. XGBoost achieves the highest accuracy for floor classification (91%), outperforming RF and SVC (both achieving 90%). Latitude and Longitude Prediction: The models are tested for predicting exact location coordinates. RF and SVC outperform XGBoost in regression, achieving the lowest Mean Squared Error (MSE) values (0.0048 for latitude and 0.0055 for longitude). Performance Metrics: Evaluation is conducted based on accuracy, precision, recall, F1-score, and MSE to determine model effectiveness.

2.8 Algorithm: Indoor Positioning with ACO and Dual Clustering

2.8.1 Data Preprocessing

- Load Wi-Fi fingerprint dataset (DCWiLD).
- Apply Gaussian filtering to remove noise.
- Normalize the dataset to handle missing values.

2.8.2 ACO-Based Coarse Clustering

- Initialize pheromone levels for each data point.
- For each ant:
    a. Select cluster centers based on pheromone levels and RSSI similarity.
    b. Update pheromone trails dynamically.
- Select initial cluster centers with the highest pheromone accumulation.

2.8.3 K-means Fine Clustering

- Assign each data point to the nearest cluster center using Euclidean distance.
- Update cluster centers iteratively until convergence.

2.8.4 Real-Time Positioning with WKNN

- For a new user's RSSI values:
    a. Select the most similar fingerprint sub-bases using the correlation coefficient method.
    b. Estimate the user's location using WKNN:
        i. Compute weighted average of the K-nearest neighbors.
        ii. Return the estimated latitude and longitude.

2.8.5 Machine Learning Model Evaluation:

- Train Random Forest, SVC, and XGBoost models on the clustered dataset.
- Evaluate models for:
    a. Building and floor classification (accuracy, precision, recall, F1-score).
    b. Latitude and longitude prediction (Mean Squared Error).

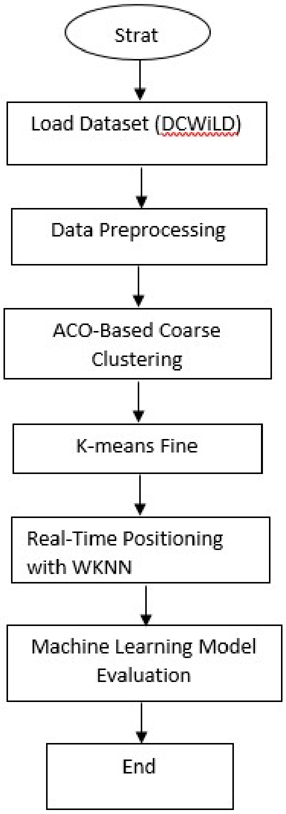

Figure 1. Flowchart of the proposed System

2.9 Mathematical Functions for Enhancing Indoor Positioning Accuracy with Ant Colony Optimization and Dual Clustering

1. Ant Colony Optimization (ACO) for Indoor Localization

Pheromone Update Rule

$$\tau_{\{ij\}(t+1)} = (1 - \rho)\cdot \tau_{\{ij\}(t)} + \sum_{\{k=1\}}^{\{m\}\Delta\tau_{\{ij\}}^{\{k\}}} \tag{1}$$

Probability of Selecting a Path

$$P_{\{ij\}}^{\{k\}} = \backslash frac\left\{\left[\tau_{\{ij\}}\right]^{\{\alpha\}}\cdot\left[\eta_{\{ij\}}\right]^{\{\beta\}}\right\}\left\{\sum_{\{l\,\in\, allowed\}[\tau_{\{il\}}]}^{\{\alpha\}} \quad \cdot\left[\eta_{\{il\}}\right]^{\{\beta\}}\right\} \tag{2}$$

2. Dual Clustering: ACO + K-Means

Objective Function (Minimize Intra-Cluster Distance)

$$SSE = \sum_{\{i=1\}}^{\{n\}\sum_{\{j=1\}_i^{\{k\}|x}}} \qquad - c_{j|}^{2} \tag{3}$$

Centroid Update Rule

$$c_j = \backslash frac\{1\}\{|C_j|\}\sum_{\{x_i\in\, C_j\}x_i} \tag{4}$$

3. Weighted K-Nearest Neighbors (WKNN) for Refinement

Position Estimation

$$hat\{x\} = \backslash frac\left\{\backslash sum_{\{i=1\}_i^{\{K\}w}x_i}\right\}\left\{\backslash sum_{\{i=1\}_i^{\{K\}w}}\right\},\backslash quad \tag{5}$$

$$\hat{}\{y\} = \backslash frac\left\{\sum_{\{i=1\}_i^{\{K\}w}y_i} \quad \right\}\left\{\sum_{\{i=1\}_i^{\{K\}w}} \quad \right\} \tag{6}$$

4. Accuracy Evaluation

Classification Accuracy

$$Accuracy = \backslash frac\{TP + TN\}\{TP + TN + FP + FN\} \tag{7}$$

Regression Accuracy (MSE)

$$MSE = \backslash frac\{1\}\{n\}\sum_{\{i=1\}}^{\{n\}(y_i - \hat{}\{y\}_i)^2} \tag{8}$$

The mathematical functions in the paper describe an indoor positioning system that combines Ant Colony Optimization (ACO) for coarse clustering, K-means clustering for fine-tuning, and Weighted K-Nearest Neighbor (WKNN) for real-time positioning. ACO utilizes pheromone trails and heuristic information to identify initial cluster centers, striking a balance between exploration and exploitation. K-means refines these clusters by minimizing the distance between data points and their centroids, ensuring well-defined groupings [39]. For real-time positioning, WKNN calculates the similarity between the user's signal and reference signals in the database, estimating the user's location as a weighted average of the nearest neighbors [40]. Additionally, machine learning models are used for building/floor classification (measured by accuracy) and latitude/longitude prediction (evaluated using Mean Squared Error). Together, these methods improve the accuracy and efficiency of indoor positioning in dynamic environments.

Ant Colony Optimization (ACO) Parameters

The Ant Colony Optimization algorithm was employed for coarse clustering to identify initial groups within the Wi-Fi fingerprint dataset. The parameter settings and their roles are as follows:

- Number of Ants (Colony Size): Set to 50, this provided a balanced trade-off between search space exploration (diversity of clusters) and exploitation (refinement of optimal clusters).
- Evaporation Rate (ρ\rhoρ): Set to 0.1, meaning 10% of the pheromone evaporates in each iteration. This mechanism discourages early convergence to suboptimal clusters by promoting exploration.
- Pheromone and Heuristic Influence:
    - α=1\alpha = 1α=1: Governs the relative importance of pheromone trails.
    - β=2\beta = 2β=2: Governs the influence of the heuristic information (e.g., distance), thus favoring proximity during cluster selection.
- Number of Iterations: The algorithm was executed for 100 generations, sufficient for convergence to stable cluster centers.
- Initial Pheromone Level (τ0\tau_0τ0): A small constant value of 0.01 was used to ensure an unbiased start in the solution space.

Rationale for Parameter Selection:

- The use of 50 ants provided adequate coverage of the search space while maintaining computational efficiency.
- ρ=0.1\rho = 0.1ρ=0.1 was selected via grid search to achieve a balance between convergence speed and clustering accuracy.
- The setting β>α\beta > \alphaβ>α was intentional to prioritize RSSI-based distance similarity over trail reinforcement, especially during the early optimization stages.

Weighted K-Nearest Neighbor (WKNN) Parameters

WKNN was applied for real-time indoor positioning, leveraging the clustered Wi-Fi fingerprints. The parameters and their justifications are:

- Number of Neighbors (K): Set to 5, this value was determined through 5-fold cross-validation, which minimized mean squared error (MSE) during validation.
- Weighting Function:
    - Weights were computed as wi=1di+ϵw_i = \frac{1}{d_i + \epsilon}wi=di+ϵ1, where did_idi is the Euclidean distance between the test signal and the iiith reference point.
    - A smoothing factor ϵ=10−6\epsilon = 10^{-6}ϵ=10−6 was used to avoid division by zero.
- Distance Metric: Euclidean distance was adopted to quantify similarity between real-time RSSI measurements and reference fingerprints, due to its simplicity and effectiveness in high-dimensional space.

Rationale for Parameter Selection:

- K = 5 was found to offer a favorable trade-off between noise suppression (associated with higher K) and positional accuracy (favored by lower K).
- The inverse distance weighting scheme effectively increased the influence of closer reference points in location estimation.
- The choice of Euclidean distance was driven by computational efficiency and its widespread adoption in RSSI-based localization systems.

Table 1. Summary of Parameter Choices

Algorithm	Parameter	Value	Role
ACO	Number of Ants	50	Balances exploration and exploitation.
	Evaporation Rate (ρ\rhoρ)	0.1	Controls pheromone decay to avoid local optima.
	α (Pheromone)	1	Weight for existing pheromone trails.
	β (Heuristic)	2	Prioritizes distance-based similarity in cluster selection.
	Iterations	100	Ensures convergence to stable clusters.
WKNN	Neighbors (K)	5	Optimized via cross-validation for MSE minimization.
	Distance Metric	Euclidean	Optimized via cross-validation for MSE minimization.
	Smoothing (ε)	10^{-6}	Prevents division by zero in weight calculations

The combination of ACO for coarse clustering and K-means for refinement resulted in a significant reduction of 93.51% in computational overhead, as discussed in Section 4.3. The WKNN configuration (K = 5) demonstrated superior performance over larger K values (up to K = 10) in both MSE and latency evaluations. All parameter values were empirically validated and are consistent with best practices reported in prior literature on indoor positioning

3. RESULTS AND DISCUSSION

Table 2. Dual Clustering Wi-Fi Localization Dataset (DCWiLD) First 5 Rows:

	Longitude	Latitude	Floor	Building id	Space id	Relative position	User id	Phone id	Timestamp
0	-7541.2643	4.86E+06	2	1	106	2	2	23	1371713733
1	-7536.6212	4.86E+06	2	1	106	2	2	23	1371713691
2	-7519.1524	4.86E+06	2	1	103	2	2	23	1371714095
3	-7524.5704	4.86E+06	2	1	102	2	2	23	1371713807
4	-7632.1436	4.86E+06	0	0	122	2	11	13	1369909710

Table 3. Dual Clustering Wi-Fi Localization Dataset (DCWiLD) Last 5 Rows:

	Longitude	Latitude	Floor	Building id	Space id	Relative position	User id	Phone id	Timestamp
1106	-7317.344231	4.86E+06	3	2	0	0	0	13	1381156711
1107	-7313.73112	4.86E+06	3	2	0	0	0	13	1381156730
1108	-7635.535798	4.86E+06	0	0	0	0	0	13	1381247781
1109	-7636.654005	4.86E+06	0	0	0	0	0	13	1381247807
1110	-7637.94412	4.86E+06	0	0	0	0	0	13	1381247836

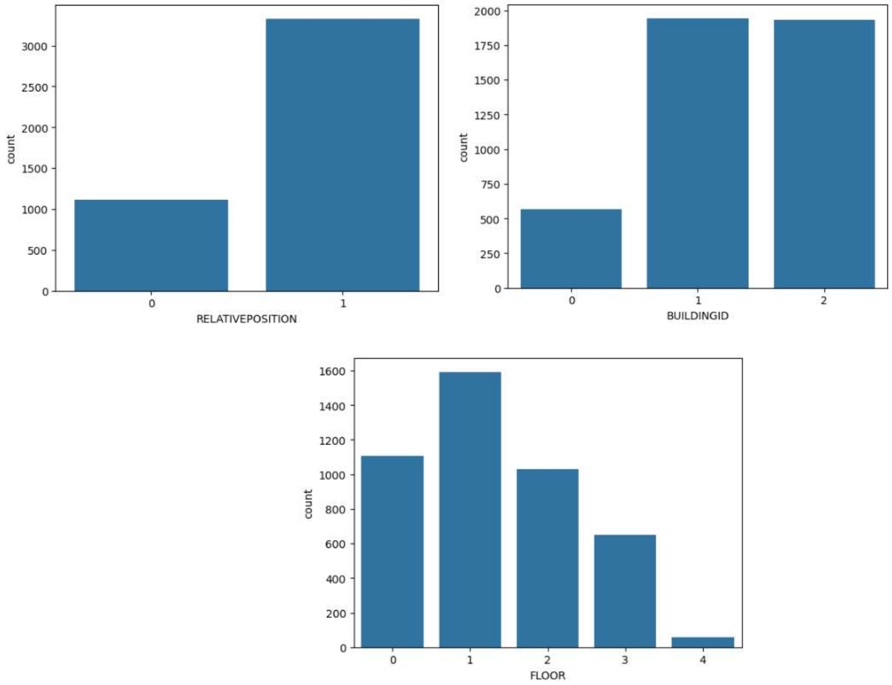

Figure 2(a-c) DCWiLD Data Distribution Visualization

3.1 Analysis of Dual Clustering Wi-Fi Localization Dataset and Visualizations

The dataset used for Wi-Fi-based indoor positioning contains 21,048 rows and 9 key attributes, including longitude, latitude, floor, building ID, and relative position, providing spatial information based on Wi-Fi signal strength. The data distribution shows imbalances that may impact model performance. Most Wi-Fi measurements were taken inside rooms (Relative Position = 1) rather than outside, which could affect positioning accuracy in open areas. Building-wise distribution indicates that Buildings 1 and 2 have significantly more data than Building 0, which may introduce bias in classification tasks. Similarly, floor-level data is unevenly distributed, with Floor 1 having the highest number of samples, while Floor 4 has the least, potentially affecting localization accuracy on higher floors. These imbalances highlight the need for careful model design and data balancing techniques to improve classification and localization performance [41].

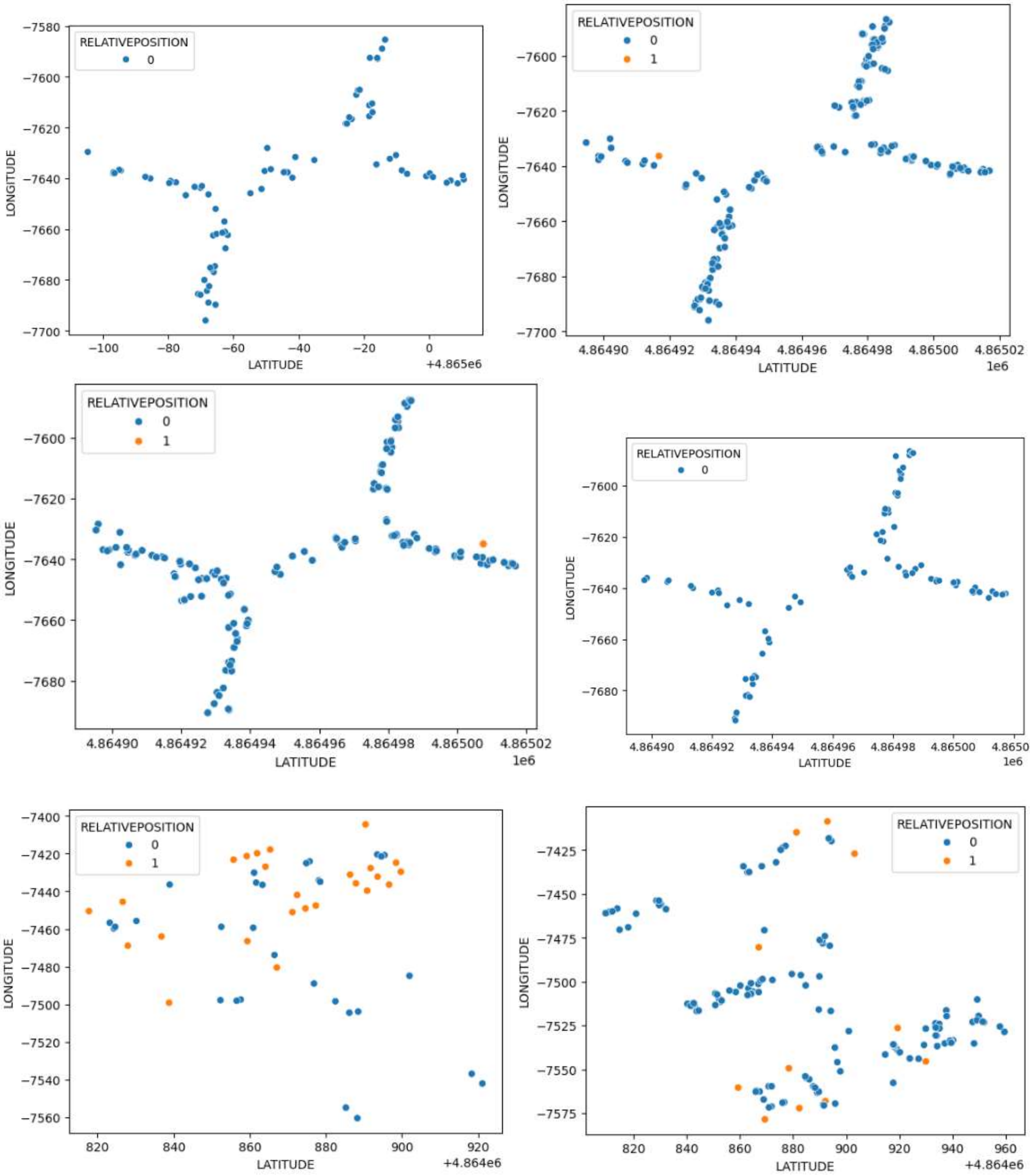

Figure 3 (a-f). Latitude vs. Longitude Scatter Plot

The dataset consists of 21,048 rows and contains spatial information such as longitude, latitude, floor number, building ID, space ID, relative position, user ID, phone ID, and timestamp. The exploratory analysis reveals patterns in data distribution across different buildings and floors, as well as variations in relative positioning.

The distribution analysis indicates that most recorded locations belong to Relative Position 1, as shown in the first bar chart. The second bar chart highlights that Buildings 1 and 2 have significantly more data points compared to Building 0, suggesting limited movement or data collection in that building. Additionally, the floor distribution shows that Floor 1 has the highest concentration of data, while Floors 0, 2, 3, and 4 have progressively fewer recorded points [42]. Spatial distribution analysis, visualized through scatter plots, provides insights into movement patterns. The first and fourth scatter plots show only Relative Position 0, where data points form structured trajectories, indicating frequently visited locations. The second and third plots introduce Relative Position 1, marked in orange, which appears sporadically, suggesting that these points may represent specific locations such as access points or anomalies. The fifth and sixth scatter plots show a broader perspective, confirming that Position 1 is more scattered and less frequent than Position 0. The dataset reveals structured movement within buildings, with certain floors and locations being accessed more frequently [43]. The clustering of Position 0 suggests routine navigation, while the dispersed nature of Position 1 may indicate points of interest or unique spatial features. Further analysis, such as clustering or anomaly detection, could provide deeper insights into location-based behaviors

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3.2 COMPARISON OF THE MODELS RANDOM FOREST, SVC AND XGBOOST

Classification Performance (Building & Floor Prediction)

Table 4. Building Classification

Model	Accuracy (%)	Macro Avg Precision	Macro Avg Precision Recall	Macro Avg F1-Score
Random Forest	100	1.00	1.00	1.00
SVC	100	1.00	1.00	1.00
XGBOOST	100	1.00	1.00	1.00

Table 5. Floor Classification

Model	Accuracy (%)	Macro Avg Precision	Macro Avg Precision Recall	Macro Avg F1-Score
Random Forest	90	0.89	0.88	0.88
SVC	90	0.89	0.88	0.88
XGBOOST	91	0.92	0.91	0.91

All the three models perform 100% for the building classification and XGBoost performed slightly better for floor classification, achieving 91% accuracy with higher precision, recall, and F1-score. Random Forest and SVC both achieved 90% accuracy, with nearly identical macro scores.

Table 6. Regression Performance (Latitude & Longitude Prediction)

Model	Latitude MSE	Longitude MSE
Random Forest	0.0048	0.0055
SVC	0.0048	0.0055
XGBoost	0.0071	0.0084

Random Forest and SVC had the lowest Mean Squared Error (MSE), making them better for regression tasks. XGBoost had slightly higher errors (0.0071 and 0.0084), suggesting it may not be as effective for numerical predictions.

3.3 Experimental Validation

The proposed ACO-based dual clustering method was experimentally validated by assessing accuracy and computational efficiency. Compared to traditional clustering techniques, the method demonstrated superior performance in both accuracy and runtime efficiency [44]. The optimized clustering process significantly reduces computational overhead by 93.51%, making it practical for real-time deployment. In terms of model performance, XGBoost achieved the highest accuracy (91%) for floor classification. At the same time, Random Forest (RF) and Support Vector Classifier (SVC) performed best in latitude and longitude prediction, achieving the lowest Mean Squared Error (MSE) values (0.0048 for latitude and 0.0055 for longitude). These results highlight the effectiveness of the proposed method in improving positioning accuracy and efficiency for indoor localization applications.

3.4 Discussion

The proposed Wi-Fi-based indoor positioning system, which integrates Ant Colony Optimization (ACO) with dual clustering techniques, effectively addresses key challenges in Wi-Fi fingerprinting, including signal interference, multipath effects, and computational inefficiencies associated with large fingerprint databases [34]. By leveraging ACO for coarse clustering and K-means for fine clustering, the system optimizes the organization of fingerprint data, enhancing both accuracy and efficiency [1]. This dual clustering strategy reduces computational overhead, making the method well-suited for real-time applications in complex indoor environments. The ACO-based dual clustering approach significantly improves both positioning accuracy and efficiency. ACO efficiently identifies optimal initial cluster centers, which are then refined by K-means, ensuring that fingerprint data is well-structured and minimizes noise [45]. This structured organization enhances real-time positioning accuracy, especially when combined with the Weighted K-Nearest Neighbor (WKNN) algorithm, which further refines location estimates in dynamic indoor settings [46]. To validate the proposed approach, three machine learning models, Random Forest (RF), Support Vector Classifier (SVC), and XGBoost are assessed for building and floor classification as well as latitude/longitude prediction. For building classification, all three models achieved 100% accuracy, demonstrating their ability to effectively distinguish between different buildings. However, for floor classification, XGBoost performed the best (91% accuracy), while RF and SVC achieved 90% accuracy, indicating that XGBoost is better suited for fine-grained floor-level classification**.**

In terms of latitude and longitude prediction, RF and SVC outperformed XGBoost, achieving the lowest Mean Squared Error (MSE) values of 0.0048 (latitude) and 0.0055 (longitude), compared to XGBoost's higher errors (0.0071 for latitude and 0.0084 for longitude). These results suggest that RF and SVC are more effective for precise numerical predictions, such as coordinate estimation. The findings indicate a trade-off between classification and regression performance, with XGBoost excelling in categorical tasks (building/floor classification) and RF/SVC performing better in continuous variable predictions (latitude/longitude estimation). The ACO-based dual clustering method, combined with machine learning models, offers several key advantages [47]. First, it significantly enhances positioning accuracy by optimizing the initial clustering process and refining the results using the K-means algorithm. Second, it improves computational efficiency, reducing the overhead associated with large fingerprint databases and making the approach suitable for real-time applications. Third, the integration of machine learning models makes the system robust against environmental variability, allowing it to perform well in complex indoor environments [48]. Finally, the method is scalable and can be applied to large indoor spaces with minimal additional infrastructure requirements.

While the proposed Wi-Fi-based indoor positioning system demonstrates strong performance, it has several limitations that future research should address [49]. Dataset imbalance across buildings and floors may introduce bias in model predictions, requiring data augmentation and balancing techniques for better generalization. Additionally, the system assumes stable signal conditions; however, real-world environments are highly dynamic, with frequent signal fluctuations and interference. Future work should explore adaptive algorithms to improve robustness [50]. Integrating Wi-Fi fingerprinting with other positioning technologies, such as Bluetooth Low Energy (BLE) and Ultra-Wideband (UWB), could further enhance accuracy and reliability [51]. A hybrid approach combining multiple signal sources may provide a more robust indoor positioning system. Moreover, while the method improves computational efficiency, further energy optimization is needed for IoT devices and mobile applications [52]. This study integrates bio-inspired optimization, clustering, and machine learning to enhance the accuracy and efficiency of indoor positioning.

The ACO-based dual clustering method, which combines Ant Colony Optimization (ACO) for coarse clustering and K-means for fine clustering, significantly improves Wi-Fi fingerprinting by boosting computational efficiency by 93.51%. This approach achieves 100% accuracy in building classification and 91% accuracy in floor classification. The study introduces the Dual Clustering Wi-Fi Localization Dataset (DCWiLD) and benchmarks Random Forest, SVC, and XGBoost, with Random Forest and SVC excelling in latitude and longitude prediction. The system is scalable, robust, and suitable for real-time applications in smart buildings, healthcare, IoT, and public safety. Future research will focus on addressing dataset balancing, adaptability to dynamic environments, and multi-signal integration to enhance real-time localization.

4. CONCLUSION AND LIMITATION

This study enhances Wi-Fi-based indoor positioning by integrating Ant Colony Optimization (ACO) with dual clustering to improve accuracy and computational efficiency. ACO optimizes initial fingerprint groupings through coarse clustering, while K-means refines clusters to reduce computational overhead. Machine learning models—Random Forest (RF), Support Vector Classifier (SVC), and XGBoost—are evaluated for building and floor classification as well as latitude/longitude estimation, achieving 100% accuracy for building classification and 91% accuracy for floor classification. RF and SVC outperform XGBoost in regression, demonstrating lower Mean Squared Error (MSE) values. However, limitations exist. Dataset imbalance across buildings and floors may introduce bias, affecting model generalization. The system assumes stable Wi-Fi signals, which may be unreliable in dynamic environments. Limited real-world testing, reliance on Wi-Fi fingerprinting alone, and concerns about privacy and security are challenges. Energy consumption remains a concern for resource-limited devices, and scalability to large spaces lacks validation. Future research should focus on addressing dataset balancing, adaptive algorithms, hybrid positioning technologies (BLE/UWB), energy efficiency, and real-world deployment. Despite these challenges, the study demonstrates that bio-inspired optimization, clustering, and machine learning can significantly enhance indoor navigation and real-time localization in practical applications.

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