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Machine Learning methods for improved positioning accuracy in Bluetooth low energy asset tracking systems

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ABSTRACT

This paper presents an analysis of indoor positioning systems based on Bluetooth low energy (BLE) beacons. BLE-based systems are commonly used in asset tracking solutions due to their low power consumption, cost-effectiveness, and ability to provide real-time location data within indoor environments. The research investigates the accuracy and reliability of trilateral positioning methods under various environmental conditions, focusing on electromagnetic interference impacts. Five distinct testing scenarios were conducted with controlled placement of beacons across diverse environments: server rooms with high interference, corridors with moderate infrastructure interference, and open spaces with minimal interference. Testing was performed using multiple mobile devices to ensure consistency of results. An ensemble learning approach combining transformer architectures with specialized positioning networks was implemented, achieving a prediction confidence of 0.974 while maintaining an acceptable error rate. The findings indicate that the primary factors affecting accuracy are not merely physical obstacles but rather the predictability and stability of the signal propagation environment. The proposed methodology offers significant improvements for indoor positioning in environments where traditional GPS signals are unavailable or unreliable.

Keywords: indoor positioning, Bluetooth low energy, beacon, wireless localization, trilateration, RSSI, asset tracking, real-time location system.

INTRODUCTION

In the current era of the internet of things (IoT), object identification technology plays a crucial role in various aspects of life, contributing to significant advancements and innovation. With the growing demand for effective localization solutions, particularly in complex and dynamic environments, precise position determination is becoming a crucial element in many processes and applications.

The numerous Bluetooth low energy (BLE) beacon-based positioning systems have opened opportunities for practical implementation across various industrial sectors. In healthcare environments, asset tracking systems utilizing BLE technology enable hospitals to precisely locate critical medical equipment [1] or even patients [2]. This way of localization reduces equipment retrieval time and improves operational efficiency. Construction sites have increasingly adopted indoor positioning solutions for monitoring worker safety and tracking locations [3]. That allows supervisors to ensure compliance with safety protocols and respond quickly to emergencies in complex building structures.

Warehouse and logistics operations leverage BLE-based positioning systems for comprehensive asset management, enabling real-time tracking of inventory, automated guided vehicles, and personnel movement optimization throughout large storage facilities [4]. While mobile robots typically incorporate autonomous location mechanisms [5], BLE applications offer particular value in Industry 4.0 contexts by providing precise localization data that supports automated manufacturing processes, predictive maintenance scheduling, and seamless IoT ecosystem integration [6].

Smart City infrastructure projects have also embraced indoor positioning technologies to enhance navigation services in complex public buildings such as airports, shopping malls, and transportation hubs [7]. Valuable data is collected for optimizing space utilization and managing crowds. The versatility and cost-effectiveness of BLE beacon systems make them particularly suitable for large-scale deployments in industrial facilities where traditional GPS signals are unavailable or unreliable. BLE beacons are small devices that emit radio signals received via Bluetooth connection. When a mobile device with the appropriate application installed and running appears within a radius of up to several dozen meters, the user receives information in real-time. Beacons enable precise positioning of resources in rooms or areas where traditional methods, such as GPS systems, often fail due to weak or unavailable satellite signals [8].

This article aims to examine and evaluate the use of BLE beacon solutions for determining the position of resources in various environments, to design and implement a dedicated system architecture, and to develop a practical solution that can be applied in real-life conditions.

BACKGROUND

Indoor localization using trilateration and received signal strength indication (RSSI) signals is an intensively developing research area. Research presented in [9] showed that under controlled conditions, trilateration achieves an average error of 2.30 m, while extending the system to multilateration allows a reduction of this error to 1.83 m. The authors of [10] emphasized the importance of incorporating noise signals in localization research and used noise simulation in their study. A significant breakthrough in the field was the discovery of the significant impact of antenna orientation on localization accuracy. The research team presented in [11] conducted a detailed analysis of this phenomenon, proving that considering antenna orientation in localization algorithms leads to a significant improvement in positioning accuracy. BLE beacon technology has emerged as a particularly promising solution for indoor positioning applications. Research [12] demonstrated that BLE-based positioning systems can achieve sub-meter accuracy in controlled environments, with their proposed algorithm showing significant improvements over traditional proximity-based methods. The study highlighted the importance of environmental calibration and adaptive signal processing for different indoor scenarios. In the area of signal processing, an advanced convolutional network architecture with a self-attention mechanism are also proposed [13]. This solution achieved a 37.4% improvement in channel state information reconstruction accuracy in indoor conditions and 32.5% in outdoor conditions. The impact of electromagnetic interference on indoor positioning accuracy has been studied in [14]. Researchers investigated how various sources of interference, including Wi-Fi networks, electronic devices, and building infrastructure, affect RSSI-based localization systems. Their findings revealed that interference patterns are often predictable and can be compensated through adaptive filtering techniques, leading to improved positioning stability in complex electromagnetic environments. Significant progress has also been made in the field of hybrid solutions. In article [15], authors developed a novel approach combining classical trilateration methods with machine learning models. The described system not only demonstrated excellent adaptation to embedded device hardware limitations but also significantly improved localization accuracy in challenging environmental conditions. An interesting solution utilizing ensemble learning for indoor positioning has demonstrated remarkable potential for enhancing localization reliability. In [16], a multi-classifier ensemble approach is proposed that combines different positioning algorithms and sensor modalities, achieving positioning accuracies comparable to those presented in this research. Their ensemble method demonstrated particular effectiveness in environments with varying interference levels, showing improved robustness compared to single-algorithm approaches. Mobile robot-assisted localization represents another promising approach for wireless sensor networks. Research has demonstrated that mobile robots equipped with GPS can effectively reduce localization costs while improving accuracy through strategic path planning algorithms. Studies have shown that dynamic algorithms, such as LDF (least distance first) and MMNF (maximum marginal neighbouring first), can achieve better performance than traditional static path methods, with LDF demonstrating superior precision in node localization tasks [17]. The latest trends in indoor localization indicate the growing importance of transformer architectures [18]. The presented results showed that transformers are particularly effective in capturing complex temporal-spatial dependencies in RSSI signals, which translates into better localization accuracy in dynamically changing conditions.

Trilateration-based techniques are very often used in the process of improving localization accuracy, as described in [19]. Trilateration is a method of determining the position of a point in space or on a plane by measuring distances from three known reference points [20]. In the context of node localization using Bluetooth beacons, three access points with known coordinates are used to determine the position of the end device [21].

Mathematically, the problem can be represented as a system of equations:

$$(x - x_1)^2 + (y - y_1)^2 = d_1^2 \tag{1}$$

$$(x - x_2)^2 + (y - y_2)^2 = d_2^2 \tag{2}$$

$$(x - x_3)^2 + (y - y_3)^2 = d_3^2 \tag{3}$$

where: (x, y) – sought position, (x_i, y_i) – known beacon coordinates, d_i – distances calculated based on RSSI.

Distances are calculated according to the formula [11]:

$$d = 10^{\frac{-57-RSSI}{10n}} \tag{4}$$

where: $RSSI$ – received signal strength value in dB, n – attenuation coefficient, 57 is the reference $RSSI$ value read from the beacon's UI at 1 meter distance.

To solve the nonlinear system of Equations 1–3, linearization is performed by subtracting Equation 3 from Equations 1 and 2, resulting in:

$$\begin{aligned} &2(x_3 - x_1)x + 2(y_3 - y_1)y = \\ &= (d_1^2 - d_3^2) + (x_3^2 - x_1^2) + (y_3^2 - y_1^2) \end{aligned} \tag{5}$$

$$\begin{aligned} &2(x_3 - x_2)x + 2(y_3 - y_2)y = \\ &= (d_2^2 - d_3^2) + (x_3^2 - x_2^2) + (y_3^2 - y_2^2) \end{aligned} \tag{6}$$

This linearized system can be expressed in matrix form as AX = B, where:

$$A = \begin{bmatrix} -2(x^1 - x^3) & -2(y^1 - y^3) \\ -2(x^2 - x^3) & -2(y^2 - y_3) \end{bmatrix} \tag{7}$$

$$X = \begin{bmatrix} x \\ y \end{bmatrix} \tag{8}$$

$$B = \begin{bmatrix} (d_1^2 - d_3^2) - (x_1^2 - x_3^2) - (y_1^2 - y_3^2) \\ (d_2^2 - d_3^2) - (x_2^2 - x_3^2) - (y_2^2 - y_3^2) \end{bmatrix} \tag{9}$$

The solution of the equation system $X = A^{-1}B$ can be found using the matrix inversion method, which is implemented in the numpy library [22]. The solution of this equation makes it possible to finally determine the (x, y) of the localized device.

It is very important to precisely define the role of RSSI at this stage. RSSI is a measure of the radio signal power received by a device. In the context of an indoor localization project, RSSI plays a key role in determining the approximate distance between a mobile device and Bluetooth beacons [23]. RSSI is expressed in decibel-milliwatts (dB) and typically takes negative values, where values closer to zero indicate a stronger signal. For example, -50 dB indicates a stronger signal than -70 dB. The relationship between RSSI and distance is not linear and can be disrupted by various environmental factors, such as physical obstacles or electromagnetic interference [24]. To improve localization accuracy, the system uses advanced algorithms that process raw RSSI values.

However, traditional RSSI-based localization methods suffer from significant limitations that affect their practical applicability. The inherent variability and instability of RSSI measurements, combined with multipath propagation effects and signal attenuation in indoor environments, often result in poor localization accuracy and unreliable position estimates. Additionally, the non-linear relationship between RSSI and distance makes it challenging to establish consistent distance-to-signal strength mappings across different environmental conditions.

The main contributions of this manuscript include: the ensample algorithm based on a deep neural network, specifically designed to process RSSI fingerprinting data and automatically learn complex spatial patterns in indoor environments; the introduction of an adaptive signal processing framework that compensates for temporal variations and environmental interference in real-time; comprehensive experimental validation demonstrating significant accuracy improvements.

Therefore, this article proposes the use of deep neural networks to address these limitations and improve the robustness and accuracy of indoor localization systems by learning complex patterns in RSSI data and automatically compensating for environmental disturbances.

This new method allows to improve the accuracy of localization in environments where there are a lot of sources of interference, the RSSI signal intensity varies over time at a given point and thus the process of localizing an object may be subject to unacceptable error. The method proposed in the paper was compared in real conditions with the classical triliteration-based localization method. In addition, the model used in the proposed approach was compared with three models known from the literature.

PROPOSED METHODS OPTIMIZING POSITION DETERMINATION

Accurate indoor positioning is a key technical challenge in the field of localization systems. The presented system integrates traditional signal processing methods with modern deep learning solutions. RSSI signals are characterized by significant variability over time, which is particularly noticeable in the indoor environment. In the mobile application implementation, a moving average technique was applied as the first stage of RSSI signal processing. The application collects readings from BLE beacons in real-time and performs smoothing of RSSI values using a time window of 5 samples, where each sample represents a single RSSI measurement taken at discrete time intervals.

Another important aspect that has a key impact on improving localization accuracy is Outlier Exclusion. In indoor localization, proper handling of outliers plays a key role. The outlier identification system is based on the z-score method applied to position predictions from ensemble models [25]. For each prediction, a z-score coefficient is calculated, which determines its deviation from the mean of all predictions.

The outlier exclusion algorithm performs the following mathematical operations:

- Collecting predictions from ensemble models:

$$P = \{pos_1, pos_2, \ldots, pos_n\},\quad C = \{conf_1, conf_2, \ldots, conf_n\} \tag{10}$$

where: $pos_i = (x_i, y_i)$ represents the predicted 2D coordinates from the i-th model and $conf_i$ represents the confidence score of the i-th prediction.

- Detecting outliers using the z-score method:

$$z_i = \frac{|pos_i - \mu|}{\sigma} \tag{11}$$

where: μ is the average of all predicted coordinates, and σ is the standard deviation of all predicted positions

- Filtering outliers:

$$m_i = \begin{cases} 1, if\ z_i < 2 \\ 0, otherwise \end{cases} \tag{12}$$

where: positions with $z\text{-}score \geq 2$ are considered outliers and removed (applying the 2-sigma rule for outlier detection).

- Aggregating results considering prediction certainty:

$$w_i = \frac{e^{conf_i \times m_i}}{\sum_{j=1}^{N} e^{conf_j \times m_j}} \tag{13}$$

where only filtered positions from step 3 are used in the weighted average calculation.

- Calculating the final position:

$$pos_{final} = \sum_{i=1}^{N} w_i \times pos_i \tag{14}$$

where: pos_{final} represents the final estimated coordinates obtained as a weighted sum of all filtered predictions, with each prediction pos_i multiplied by its corresponding normalized weight w_i from Equation 13.

- Estimating the uncertainty of the final result:

$$uncertainty = std(P_{valid}) \quad confidence = e^{-uncertainty} \tag{15}$$

where: $std(P_{valid})$ is the standard deviation of all filtered position predictions and confidence is the final confidence score calculated using an exponential decay function that converts uncertainty into a confidence value between 0 and 1.

Positioning model design

In the proposed solution, a key component of the positioning optimization process is model training. The system architecture (Figure 1) is based on an ensemble approach, integrating various modelling methods to ensure the highest precision and reliability of predictions.

This diagram illustrates a comprehensive ensemble system for bluetooth-based indoor positioning that combines multiple neural network architectures with sophisticated data processing techniques. The learning system construction is based on a hybrid ensemble model, combining an advanced neural network with expanded attention blocks (Advanced Positioning Network, Figure 3) and transformer models (Figure 2) with different configurations. The implementation used both a multilayer network enriched with Multi Head Attention mechanisms and residual blocks, as well as dedicated transformer architectures with varying numbers of layers (4 and 6) and attention heads (4 and 8).

Enhanced Data Augmentation refers to advanced techniques for artificially expanding and improving the training dataset from the input RSSI and TRIL (trilateration) data. The system employs Gaussian Noise addition to simulate real-world signal variations and measurement uncertainties [26], Selective Dropout that randomly removes certain input features during training to improve model robustness and prevent overfitting [27], Signal Scaling that adjusts the amplitude and magnitude of RSSI values to simulate different transmission powers or distances, and RSSI Shifting that systematically shifts RSSI values to account for environmental variations like interference or hardware differences.

Advanced Aggregation represents sophisticated methods for combining predictions from multiple neural network models. Instead of simple averaging, this involves a weighted combination based on individual model confidence scores, attention-based aggregation that dynamically determines which models to trust more for specific inputs, ensemble techniques that consider model diversity and complementary strengths, and meta-learning approaches that learn optimal combination strategies.

The overall architecture trains four different neural networks in parallel, including two APN models with 256-dimensional layers and two Transformer models with the aforementioned varying configurations. Each model receives differently augmented versions of the same input data, and their outputs are intelligently combined through weighted aggregation, followed by outlier detection and uncertainty estimation to produce the final position estimate with confidence intervals. This ensemble approach leverages the strengths of different architectures and data representations to achieve more robust and accurate indoor positioning than any single model could provide.

Figure 2 presents the detailed architecture of the transformer model used in the ensemble system for Wi-Fi-based indoor positioning. The model begins with input RSSI and TRIL data that undergoes input embedding through a linear transformation from the original dimensionality to 256 dimensions, followed by layer normalization to stabilize training. The core processing occurs through a transformer encoder consisting of 6 layers, where each layer incorporates multi-head attention mechanisms with 8 attention heads that allow the model to focus on different aspects of the input signal patterns simultaneously.

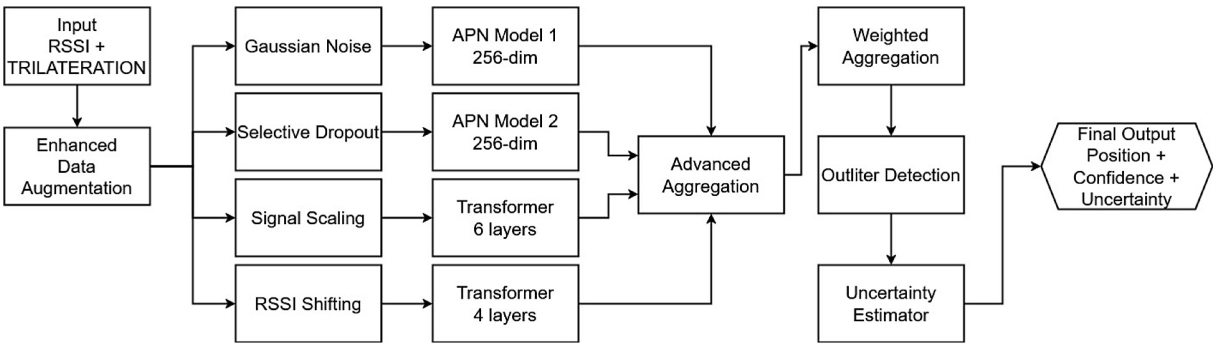

Figure 1. Overall architecture of the ensemble system combining different models and data augmentation techniques

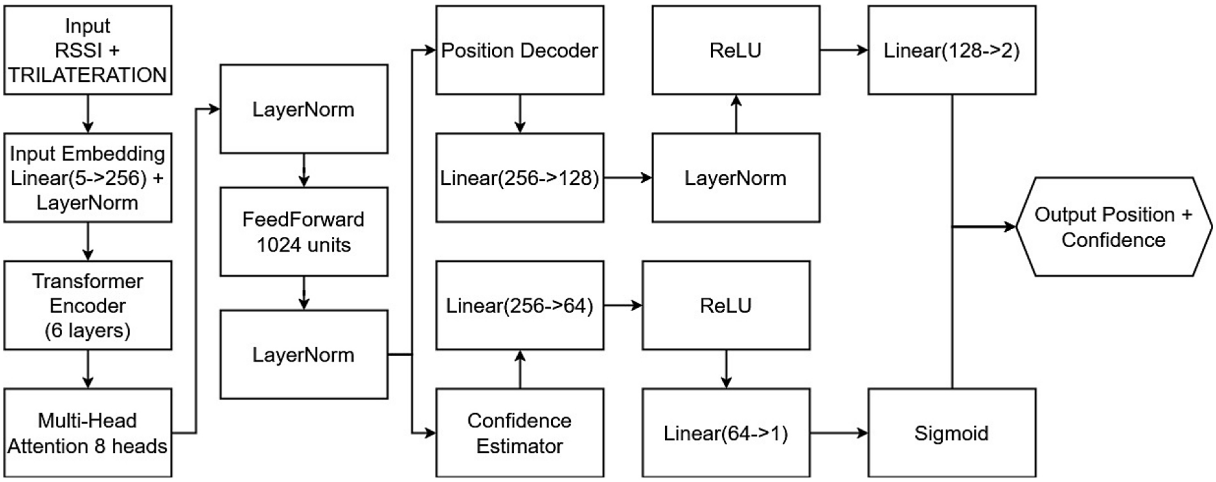

Figure 2. Architecture of the transformer model used in the system

After the transformer encoder processing, the data flows through layer normalization and a feedforward network containing 1024 units, followed by another layer normalization step. The architecture then branches into two parallel processing paths that serve distinct purposes in the positioning task. The Position Decoder path processes the transformed features through a linear layer that reduces dimensionality from 256 to 128, applies layer normalization, passes through a ReLU activation function, and finally outputs the 2-dimensional position coordinates through a linear layer with 128 to 2 transformation.

Simultaneously, the Confidence Estimator path provides uncertainty quantification by processing the same transformed features through its own linear layer, reducing from 256 to 64 dimensions, applying ReLU activation, then a linear transformation from 64 to 1 dimension, and finally a sigmoid activation function to produce a confidence score between 0 and 1. This dual-output design enables the model to not only predict position coordinates but also estimate the reliability of its predictions, which is crucial for practical indoor positioning applications where measurement quality can vary significantly due to environmental factors and signal interference.

Figure 3 illustrates the comprehensive architecture of the APN, which represents a sophisticated neural network design that combines multiple attention mechanisms with enhanced residual connections for Wi-Fi-based indoor positioning. The network processes input RSSI and TRIL data through separate pathways that eventually merge for comprehensive feature extraction and position estimation.

The architecture begins by splitting the input into two distinct processing streams. The RSSI features, containing 3 components, are processed through an RSSI Encoder consisting of a linear transformation to 256 dimensions, followed by layer normalization and an Enhanced Residual Block. Simultaneously, the TRIL features with 2 components undergo processing through a TRIL Encoder with linear transformation to 128 dimensions, layer normalization, and their own Enhanced Residual Block. Both streams then pass through Multi-Head Attention mechanisms that enable the network to focus on different aspects of the positioning-relevant information.

The two processed streams converge through a Feature Fusion layer that combines the representations using a linear transformation from 384 to 512 dimensions, followed by layer normalization and another Enhanced Residual Block. The fused representation then undergoes Global Attention processing, which provides a comprehensive view of all features, followed by dropout regularization and additional Multi-Head Attention and Enhanced Residual Block layers for deep feature refinement.

The final stage employs a multi-decoder architecture [28] where the processed features are distributed to three parallel decoders, each containing linear transformations from 512 to 2 dimensions. The outputs from these decoders are averaged to produce the position estimate, while separate branches generate confidence estimation through a linear layer from 512 to 1 dimension and uncertainty estimation through another 512 to 2 transformation. This multi-path approach with averaging provides robustness against individual

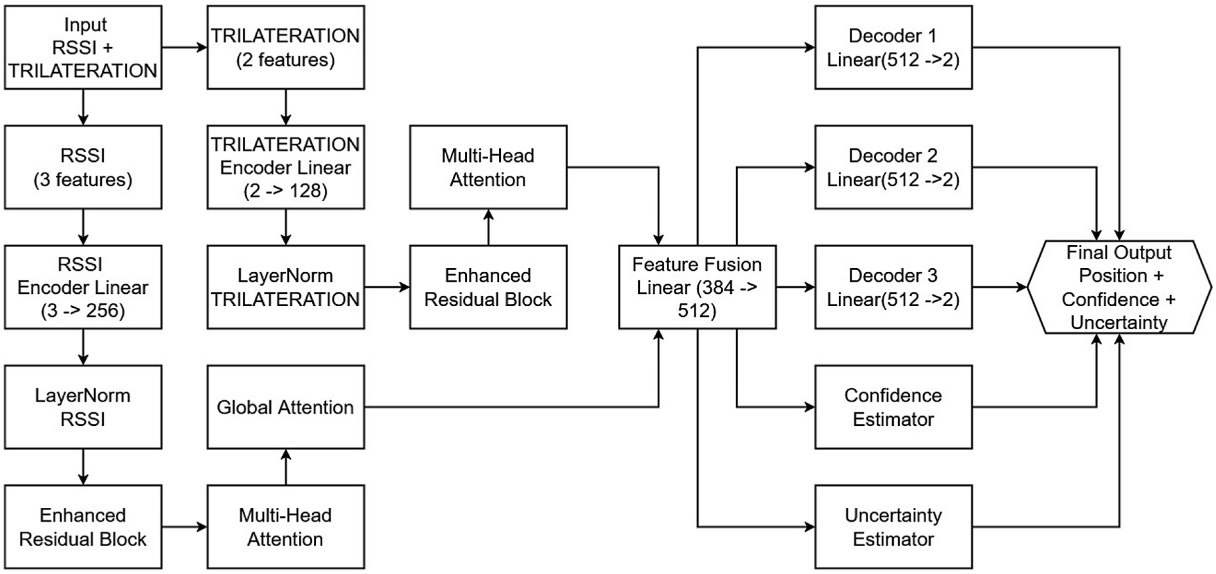

Figure 3. Architecture of the advanced positioning network (APN)

decoder errors, while the confidence and uncertainty estimation components enable the network to quantify the reliability of its predictions, making it particularly suitable for real-world indoor positioning applications where signal quality and environmental conditions can vary significantly.

TESTING IN A REAL ENVIRONMENT

As part of the research, five measurement scenarios were conducted in different locations. The aim was to assess the impact of interference on the beacon signal measurement in various environments. The selected locations were:

1. Laboratory room F602 (Figure 4b,c,d) in building of Rzeszow University of Technology (PRz) – a room with servers, network equipment and numerous computers generating electromagnetic interference.
2. Corridor on the 6th floor in the PRz building – a place with interference from infrastructure installations.
3. Open area between PRz campus buildings (P and L) – an open green space with minimal interference.
4. Parking lot between Ikar Dormitory and building H – an open outdoor space.
5. Laboratory room F604 in the PRz building – a room with a similar layout to room F602, but without a running server.

Each scenario was performed with the same arrangement of beacons and measurement points. In the Figure 4a, circles indicate beacons, and crosses indicate measurement points. In each scenario, five measurement series were performed using four different devices: RMX2202 phone (REALME GT), RMX3085 phone (REALME 8), Samsung Galaxy S22 phone, SAMSUNG Galaxy Tab A9+ tablet.

Figure 5a) demonstrates severe trilateration degradation in a complex indoor environment. The positioning estimates exhibit maximum dispersion with a coordinate range spanning approximately (-1, -2) to (3, 3) meters, indicating positioning accuracy well beyond acceptable thresholds. The scatter plot shows no convergence toward the true position (2.0, 1.0), with measurements distributed as isolated black dots indicating no statistical correlation.

The indoor propagation environment creates significant multipath fading with signal delays that corrupt ranging measurements. Signal blocking conditions dominate the transmission path, introducing positive bias in distance estimates due to excess signal loss and timing errors. The beacon configuration at coordinates (0.0, 0.0), (3.0, 0.0), and (3.0, 3.0) creates suboptimal triangulation geometry, where measurement uncertainties are amplified by the positioning algorithm's sensitivity to range errors.

Figure 5b) illustrates improved trilateration performance with measurements showing tighter clustering. The black dots are concentrated in a more compact region around coordinates (1.5, 1.0), demonstrating reduced scatter compared to

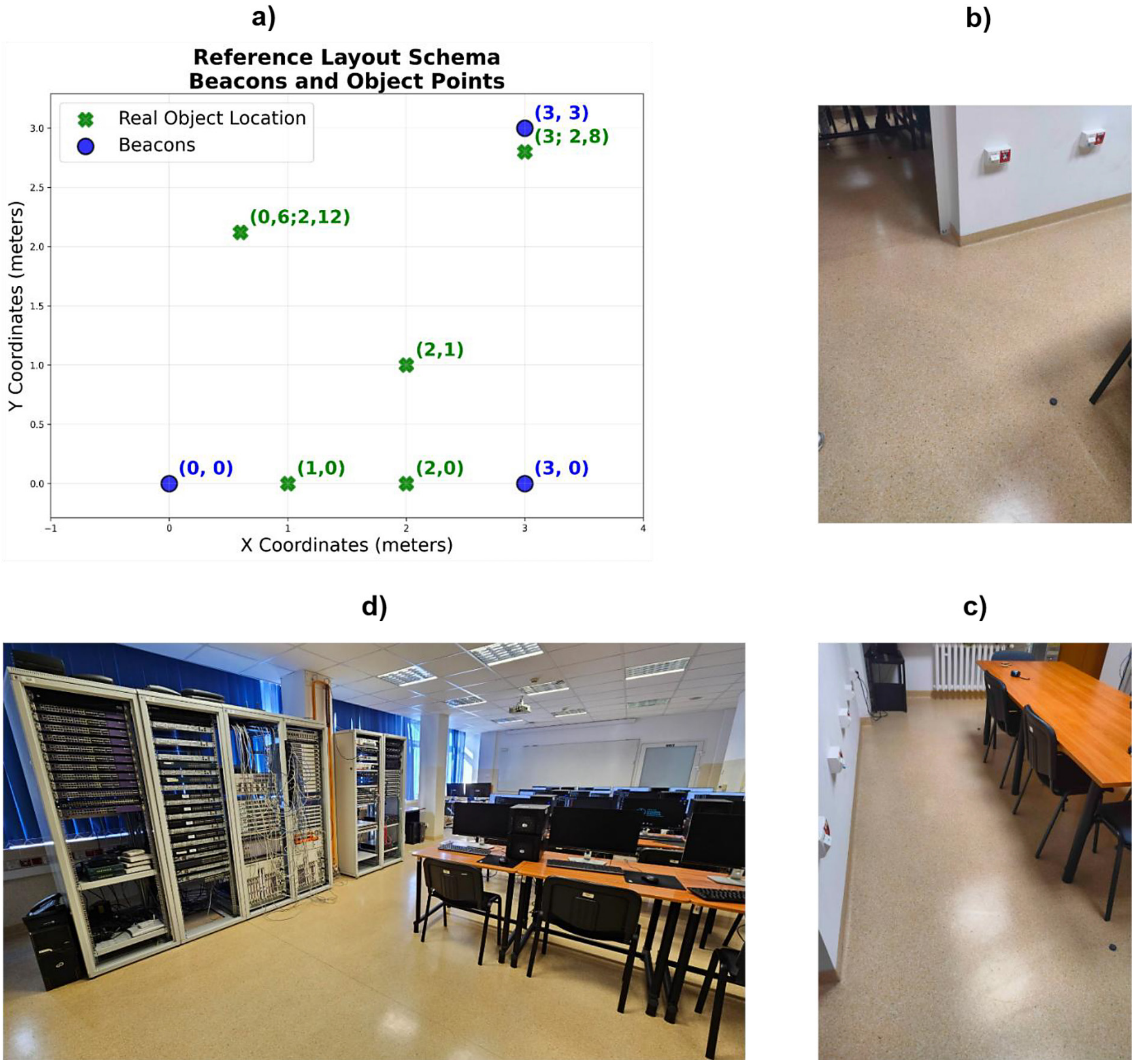

Figure 4. a) Measurement scheme; b) and c) Laboratory room F602 with beacon placement d) Full laboratory room F602

the previous scenario. This pattern reflects better signal propagation conditions that minimize ranging errors. The concentrated distribution indicates that this environment provides more favourable conditions for trilateration, with reduced multipath interference and improved signal quality that results in more consistent distance measurements and better positioning accuracy.

Figure 5c) shows trilateration measurements forming a distinct vertical clustering pattern. The black dots are arranged in a narrow vertical distribution around the x-coordinate 1.0, extending from approximately y = 0.5 to y = 2.5. This linear clustering suggests environmental constraints that affect positioning in one coordinate dimension more than the other. The vertical alignment of measurements indicates systematic effects in signal propagation that create directional bias in the positioning estimates, while maintaining reasonable accuracy in the perpendicular direction.

Figure 5d presents trilateration results with moderate scatter around the coordinate space. The black dots show a broader distribution compared to Figures 5b and 5c, but are more controlled than Figure 5a. The measurements appear clustered in the lower portion of the coordinate system around (1.0, 0.5) to (2.5, 1.5). This distribution pattern suggests intermediate environmental conditions that provide acceptable but not optimal trilateration performance, with moderate multipath effects and signal interference.

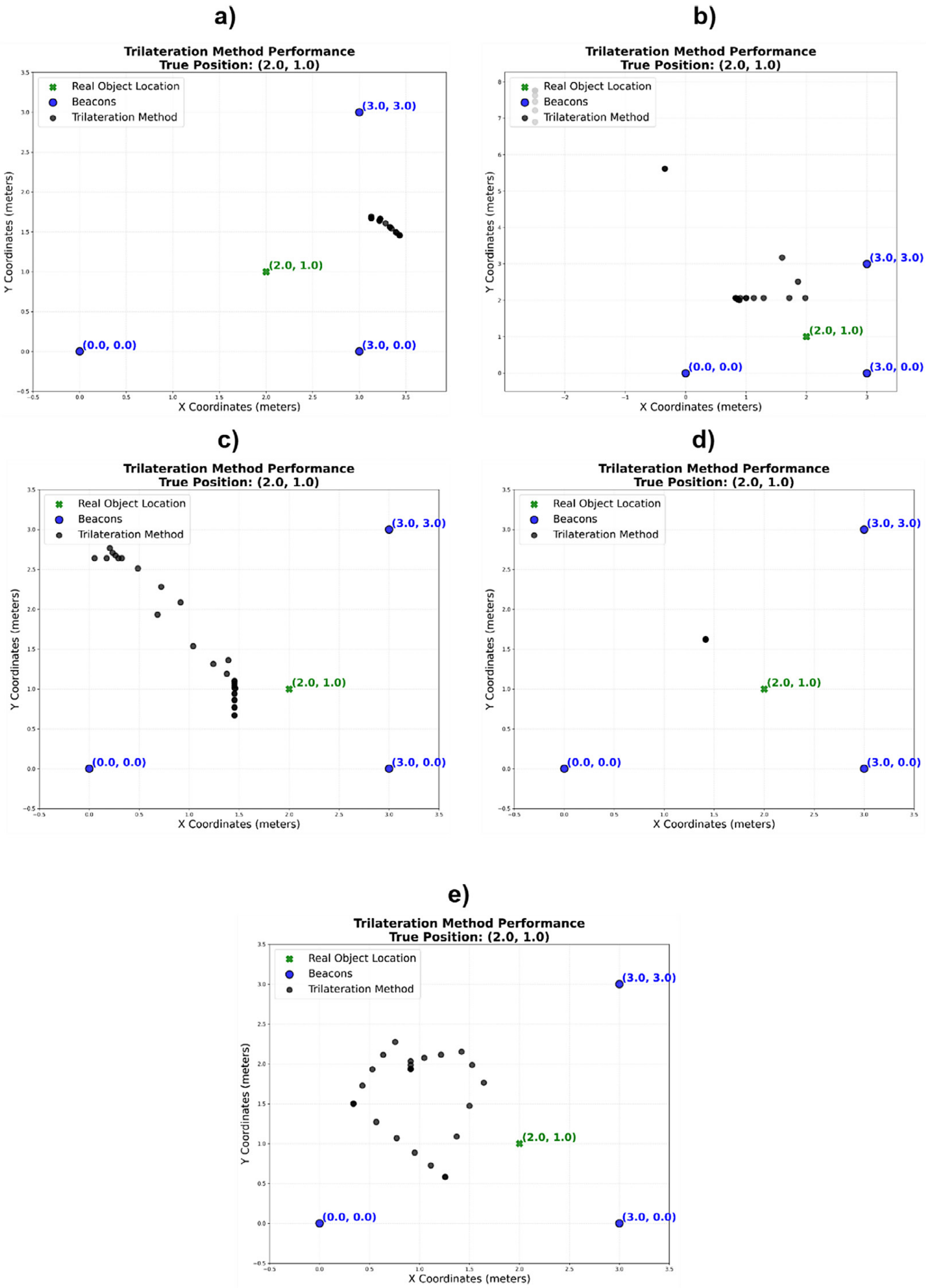

Figure 5. a) RMX2202 phone in room F602, b) RMX3085 phone in corridor, c) Samsung Galaxy S22 in open area, d) Samsung tablet on parking lot, e) RMX2202 phone in room F604

Figure 5e displays trilateration measurements with extensive scatter across the coordinate space. The black dots are distributed over a wide area from approximately (0.5, 0.5) to (3.0, 2.5), indicating significant positioning uncertainty and poor trilateration accuracy. The widespread distribution reflects challenging environmental conditions similar to Figure 5a, where multipath interference and signal degradation severely impact the reliability of distance measurements and consequently the positioning accuracy of the trilateration method. For the remaining measurement campaigns conducted across different environmental conditions and device configurations, the trilateration performance exhibited similar characteristic patterns consistent with the propagation environments tested.

Model training

The positioning system was trained using an advanced ensemble architecture combining transformer models with specialized positioning networks. Training data comprised trilateration measurements from 30-second sessions conducted at 5 locations using 4 different devices, ensuring exposure to diverse signal characteristics and hardware configurations.

This multi-device approach enables the models to generalize across different smartphone Wi-Fi chipsets, while multiple measurement locations provide comprehensive spatial coverage of the indoor environment. The diverse dataset captures the variability inherent in real-world positioning scenarios.

Training employed AdamW optimizer [29] (learning rate: 0.001, weight decay: 0.01) with Cosine Annealing scheduler and 5-fold cross-validation. This methodology produces models capable of handling device heterogeneity and spatial variations encountered in practical indoor positioning applications.

The trained models form the foundation for the performance analysis and comparison studies presented in subsequent sections (Table 1).

Test scenario with proposed method

Testing was conducted in room F602 using a single RMX2202 device to evaluate model performance under maximum interference conditions. This location was selected as it represents the most challenging signal environment identified during initial measurements.

The test scenario assesses whether the ensemble model, trained on diverse multi-device data from 5 locations, can maintain accuracy when deployed with a single device in high-interference conditions. This approach validates the model's generalization capabilities and robustness under real-world deployment constraints.

Table 1. Model training metrics

Parameter	Value
Number of epochs	15420
Final training loss	0.219
Final validation error	0.395
Average model confidence	0.974
Best validation error	0.360
Best epoch	662

Figure 6a and Table 2 compare positioning accuracy between proposed and trilateration methods under controlled conditions replicating room F602's interference environment, using a single RMX2202 device for consistency.

The deep learning method achieved significantly higher accuracy, estimating position at (3.036 m, 2.097 m) compared to the true location of (3.0 m, 2.8 m) – yielding errors of only 0.036 m and 0.703 m respectively. Standard deviations of 0.092 m and 0.124 m indicate good precision.

In contrast, trilateration showed poor accuracy despite tight clustering, estimating (1.126 m, 1.624 m) with substantial errors of 1.874 m and 1.176 m. While standard deviations (0.258 m, 0.108 m) suggest consistent measurements, the method appears to suffer from systematic bias under interference conditions.

The results demonstrate that clustering alone does not indicate superior performance - accuracy relative to ground truth is the critical metric.

Figure 6b and Table 3 examine positioning performance at point (0.6, 2.12) under the same high-interference conditions in room F602, maintaining consistency with the single RMX2202 device setup.

The proposed method estimated position at (1.474 m, -1.352 m) compared to the true location of (0.6 m, 2.12 m), resulting in errors of 0.874 m and 3.472 m, respectively. The standard deviations of 0.515 m and 1.707 m reveal moderate precision, with notable variability, particularly in the y-axis measurements.

Conversely, trilateration achieved a position estimate of (2.671 m, 1.471 m) with errors of 2.071 m and 0.649 m. The standard deviations (0.756 m, 0.505 m) demonstrate more consistent measurements than deep learning at this location, although both methods exhibit significant absolute positioning errors.

Figure 6c and Table 4 present results for point (2.0 m, 1.0 m) under identical testing conditions, revealing contrasting performance patterns.

The deep learning method delivered exceptional accuracy, estimating (2.955 m, 0.997 m) with minimal errors of 0.955 m and 0.003 m, respectively. The remarkable standard deviation of 0.0m in the y-axis indicates perfect measurement

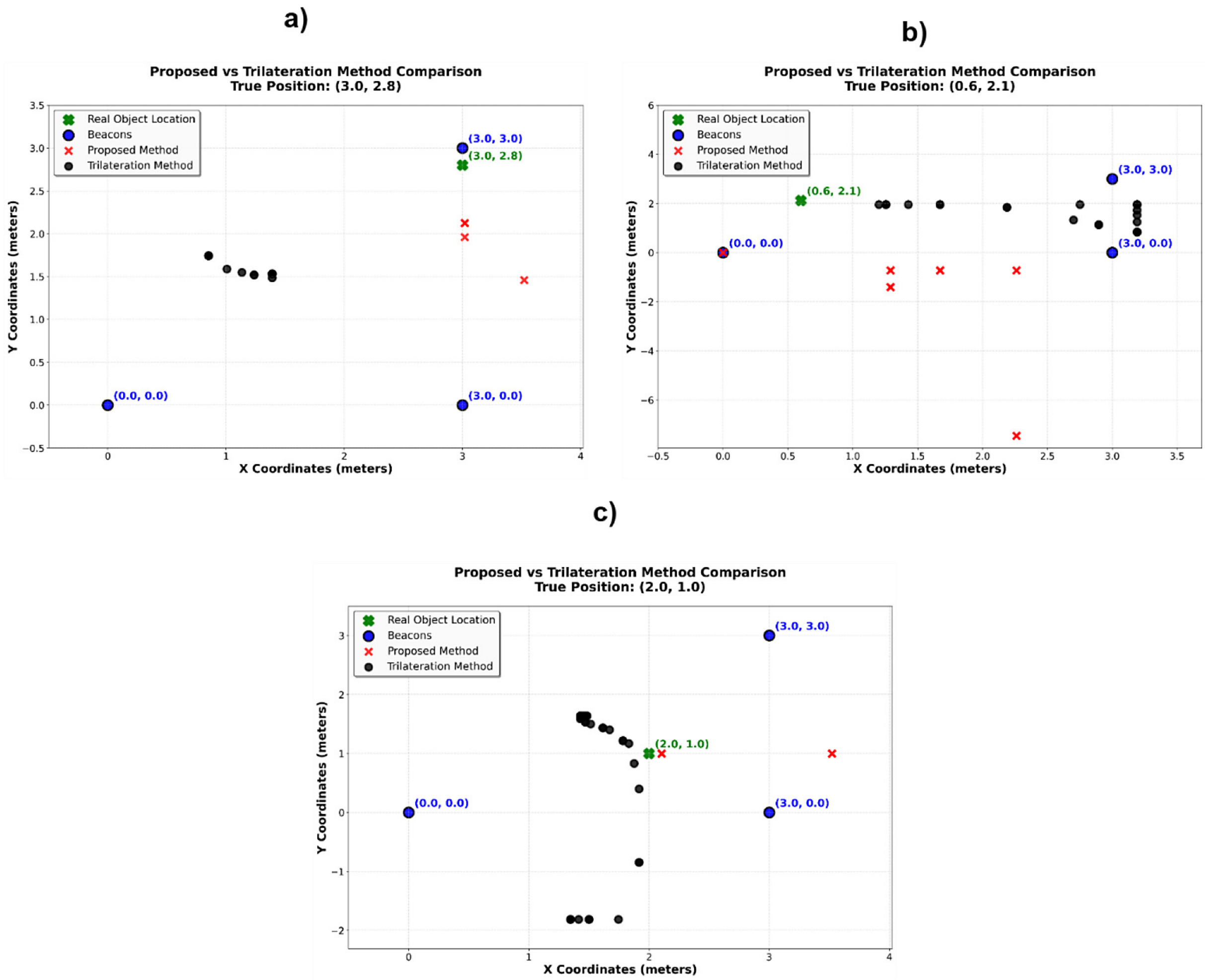

Figure 6. Example comparison of deep learning vs trilateration method results at point: a) (3, 2.8), b) (0.6, 2.12), c) (2, 1)

Table 2. Measurement metrics at point (3, 2.8) in the test scenario

Parameter	Proposed method	Trilateration method
Average trilateration at point x	3.036 m	1.126 m
Average trilateration at point y	2.097 m	1.624 m
Standard deviation at point x	0.092 m	0.258 m
Standard deviation at point y	0.124 m	0.108 m
Average RSSI for beacon 00	-76.7 dB	-58.0 dB
Average RSSI for beacon 30	-70.8 dB	-65.6 dB
Average RSSI for beacon 33	-59.0 dB	-63.967 dB

repeatability, while 0.706 m in the x-axis shows acceptable variability.

Trilateration estimated (1.564 m, 0.404 m) with errors of 0.436 m and 0.596 m. Standard deviations of 0.192 m and 1.496 m reveal excellent x-axis precision but significant y-axis instability, highlighting inconsistent performance across coordinate dimensions.

For the remaining measurement campaigns conducted using the proposed method across different environmental conditions, the positioning performance exhibited similar characteristic patterns with consistently superior accuracy compared to conventional trilateration methods.

In addition to testing in a real environment, as part of our work we also conducted a comparison

Table 3. Measurement metrics at point (0.6, 2.12) in the test scenario

Parameter	Proposed method	Trilateration method
Average trilateration at point x	1.474 m	2.671 m
Average trilateration at point y	-1.352 m	1.471 m
Standard deviation at point x	0.515 m	0.756 m
Standard deviation at point y	1.707 m	0.505 m
Average RSSI for beacon 00	-59.6 dB	-78.1 dB
Average RSSI for beacon 30	-70.1 dB	-70.5 dB
Average RSSI for beacon 33	-83.0 dB	-68.3 dB

Table 4. Measurement metrics at point (2, 1) in the test scenario

Parameter	Proposed method	Trilateration method
Average trilateration at point x	2.955 m	1.564 m
Average trilateration at point y	0. 997 m	0.404 m
Standard deviation at point x	0.706 m	0.192 m
Standard deviation at point y	0.0 m	1.496 m
Average RSSI for beacon 00	-77.3 dB	-68.4 dB
Average RSSI for beacon 30	-63.0 dB	-67.5 dB
Average RSSI for beacon 33	-71.0 dB	-72.67 dB

Table 5. Measurement metrics at point (2, 1) in the test scenario

Method	Testing setting	Reported error
Proposed method	F602 laboratory room, 3 beacons,	0.35–0.44 m
[15] Experiment No. 1 (baseline)	31m2 apartament, 5 beacons, RSSI→ML→multilateration	0.65 m average
[15] Experiment No. 23 (optimized)	31m2 apartament, tuned DNN + TFLite + multilateration	0.339 m average
[30]	36 m^2 closed room, Feed-forward neural network	1.86 m RMSE (best model, closed-room)

of the developed model with solutions proposed in the literature. The results of this comparison are presented in Table 5.

It should be noted the differences in which data were collected in the various experiments summarized in Table 5. The research conducted for the proposed method was carried out in a laboratory with a large number of working laboratory equipment, network systems and a large number of computers. The developed model was intentionally tested in such an environment in order to best evaluate its performance under real operating conditions. In the case of the systems described in papers [15, 30, 31], the tests were conducted under controlled conditions, without significant environmental interference from external sources. Despite this, the model presents very good performance for a highly disturbed environment in which the majority of validation errors are in the range of 0.35 m to 0.44 m, and the maximum model error does not exceed 0.50 m. In order to achieve such results in a variable, real-world measurement environment, it may be necessary to increase the density of the number of beacons.

CONCLUSIONS

The conducted research has shown that a BLE beacon-based localization system can achieve an average positioning accuracy of 0.35–0.44 meters under optimal conditions, which was confirmed during the model training session, where the best validation error was 0.360. However, this accuracy varies significantly depending on environmental conditions and beacon arrangement. The best results were obtained when all beacons were located in a single room, without physical obstacles between them. Under such conditions, the standard deviation of measurements was the smallest, reaching values of 0.092–0.124 m, as observed at point (3, 2.8) during tests in room F604. Analysis of results from various test scenarios revealed that the greatest challenges for the system are electromagnetic interference generated by electronic devices, physical obstacles between beacons and the receiving device, heterogeneity of the signal propagation environment, and variability of RSSI signal strength over time. The research results suggest that to achieve optimal accuracy in a typical office or laboratory room, it is recommended to place a minimum of 4–5 beacons in an area of approximately 25 m², maintaining appropriate distances between them (approximately 3–4 meters). The implementation of an ensemble model using transformer architectures proved to be an effective approach to the localization problem, achieving high prediction confidence (0.974) while maintaining an acceptable error level. Based on the achieved positioning accuracy of 0.35–0.40 meters and the insights gained from testing in various environmental conditions, several promising avenues for future investigation emerge. The research demonstrates that while sub-meter accuracy is achievable with proper beacon placement, significant improvements can still be made. The study showed that the developed method using an advanced ensemble architecture combining transformer models with specialized positioning network improves localization accuracy compared to the classic trilateration-based method. In addition, the model used in the proposed approach was compared with three models known from the literature and showed comparable or better localization accuracy. It should be noted that, unlike the methods considered in the benchmarking, the model was tested on data collected in a real environment in which there were numerous sources of RSSI signal interference.

Future work should focus on developing adaptive environmental calibration systems that can automatically adjust to specific environmental characteristics, particularly addressing the electromagnetic interference challenges observed in server rooms. Advanced deep learning architectures, including LSTM networks for temporal RSSI pattern recognition and Graph Neural Networks for modelling spatial beacon relationships, could further enhance the current ensemble transformer model's performance.

The integration of multi-modal sensor fusion combining RSSI data with accelerometer, gyroscope, and magnetometer readings would provide more robust localization, especially given the observed signal variability. Real-time implementation optimization through model compression and edge computing deployment is essential for practical applications, while uncertainty quantification techniques using Bayesian neural networks could provide confidence intervals for position estimates.

An important direction for future research involves replacing the current advanced aggregation methods with more sophisticated aggregation operators. The Choquet integral and its generalizations could provide enhanced fusion capabilities for combining multiple positioning estimates from different algorithms or sensor modalities. Particularly promising are the enhanced smooth quadrature-inspired generalized Choquet integral operators, which could better handle the nonlinear relationships and dependencies between various information sources in the ensemble model. That could potentially lead to an improved positioning accuracy and robustness in challenging electromagnetic environments.

The integration with emerging technologies such as 5G/6G and Wi-Fi 6 could provide additional data sources for improved accuracy, while energy efficiency optimization remains crucial for battery-powered beacon infrastructure. Finally, standardization efforts for interoperability between different beacon manufacturers and the development of adaptive algorithms for handling the varying signal propagation characteristics observed in different environments (indoor vs. outdoor) represent critical research directions for the widespread adoption of beacon-based deep learning localization systems.

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