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High Performance AE-CNN Model Enhanced via Gaussian Augmentation for RSSI-Dependent Indoor Positioning in Wireless Sensor Networks

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Keywords

Indoor Positioning (IP); Wireless Sensor Network; Fingerprinting; Gaussian Augmentation; AE-CNN Model; Localization Error

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RESEARCH PAPER

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Abstract

Precise indoor positioning system remains a significant challenge within Wireless Sensor Networks (WSNs) due to the instability and noise sensitivity of Received Signal Strength Indicator (RSSI) data. This paper proposes an advanced hybrid deep learning framework designed for 2D indoor localization, utilizing RSSI measurements to predict human or object position. Furthermore, to enhance the robustness of the model against signal variance and promote its generalization capability under this uncertainty, a data augmentation strategy is applied using three methods: Gaussian Noise Injection (GNI), Gaussian Mixture Model (GMM), and Bayesian Gaussian Mixture Model (BGMM). The purpose of data augmentation is to simulate actual noise and optimize the training dataset adaptability. High-accuracy architecture has been introduced that leverages an Auto-Encoder with a one-dimensional Convolutional Neural Network (AE−CNN). The Auto-Encoder acts as a noisy input filter and feature compressor, while the CNN acts as a spatial pattern extractor necessary for prediction. The original and augmented datasets were employed to train the proposed model. Its effectiveness was then tested utilizing error rate analysis and performance metrics. The best performance was achieved through Gaussian Noise Injection augmentation, yielding 98% accuracy and MSE corresponding to 0.48 m. This methodology offers a lightweight and noise-robust approach for location estimation, particularly in resource-constrained contexts where signal reliability is crucial.

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1. Introduction

With the accelerated advancement of Internet of Things (IoT) ecosystems and the emergence of industry 4.0, the digital revolution has become a critical necessity across all domains [1]. Advanced applications, including smart cities, medical care, facilities, and retail environments are being developed at an exceptional rate due to the integration of artificial intelligence algorithms, robotics systems, big data processing, and 5G technology [1,2]. A significant majority of smart device users (74%) now depend on location-based systems [1]. Moreover, as individuals spend nearly 80% of their daily life in indoor settings, 70% of smartphone usage and 80% of total data traffic occur within these environments [1]. Consequently, indoor positioning is crucial for delivering intuitive and customized user services, as well as for monitoring and control through smart devices [3]. It has become an essential component of the progress of robotics, automation, and wireless systems, demanding accurate and efficient real-time solutions; thus, the global indoor positioning market is estimated to reach $183.81 billion by the year 2027 [1]. Determining the spatial coordinates of objects or users within both external and internal

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environments is defined as localization, which can be classified into outdoor and indoor settings [1,4]. In outdoor localization, users frequently employ Global Positioning System (GPS) alongside various Global Navigation Satellite Systems (GNSS) based on the area [1]. GPS localization systems deliver effective location capabilities in open outdoor environments [1,5]. On the other hand, in enclosed environments like tunnels, buildings, and underground areas, where a straight line of sight is obstructed, their performance is suboptimal and their applicability is significantly constrained due to adverse indoor channel characteristics, such as multipath fading and shadowing [1,6,7]. The challenge in indoor positioning remains a complex task [8]. A range of signal measurement methods are available for indoor localization, which notably include Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Round-Trip Time (RTT) [4,9]. RSSI is the method that is most frequently used among these measurements [10]. Additionally, RSSI technology faces challenges such as signal fluctuation, noise, and accuracy limitations [4,10]. The number of localization errors increases due to obstructions and walls, which often decrease or weaken radio signals [4,10]. Outdoors, RSSI-based localization methods provide an acceptable level of accuracy [4]. Localization approaches in wireless sensor networks can be categorized into two paradigms: triangulation and fingerprinting [4]. Triangulation locates node coordinates by analyzing RSS data gathered from sensors placed in known fixed positions [4]. In contrast, the fingerprinting approach predicts node location by using RSSI values from stationary sensor nodes that are pre-stored in a database [4]. Fingerprint-based techniques are employed to identify the position of a device or user within a complex indoor environment [4,10]. This category of techniques has two distinct stages: an offline stage and an online stage [4,10]. During the former, a signal map (fingerprint database) is generated utilizing the signal strengths obtained from reference points to characterize the indoor settings [4,10]. Subsequently, the online stage involves gathering signal strengths from nearby access points in an unspecified place and transmitting them to the server containing the signal map [4,10]. Artificial intelligence techniques, specifically those based on machine learning and deep learning, have been extensively implemented in many applications of wireless sensor networks (WSNs) [4]. Within the context of indoor positioning, significant interest has been attributed to Deep Learning techniques due to their exceptional capability for extracting complex features compared with conventional localization methods [8]. This research focuses on enhancing indoor target localization in WSN, which has been crucial for many applications in recent years, such as item positioning in laboratories, patient monitoring in smart hospitals, industrial automation, and tracking children's positions in schools using deep learning. A wide variety of localization approaches and systems in WSNs are currently available to locate objects indoors; however, some of these systems are often expensive, difficult to use, and inaccurate in complex contexts. While numerous localization systems utilizing WSN-based fingerprinting have been introduced, their practical effectiveness remains constrained, largely due to a heavy dependence on studies conducted in simulated environments. These limitations have motivated the current work to develop a practical solution. The primary technical contributions presented in this study are outlined below:

1. Introducing a lightweight deep learning model that leverages a denoising Auto-Encoder (AE) for signal clean-up with a 1D Convolutional Neural Network (CNN) to achieve high accuracy in estimating positions.
2. The RSSI dataset was augmented via Gaussian Data Augmentation to mitigate data sparsity and improve signal diversity, simulating natural variations found in real indoor environments.
3. A detailed study was conducted through four experimental scenarios (Original, GNI, GMM, and BGMM). The results revealed that the proposed work achieved its optimal localization precision with augmentation using the Gaussian Noise Injection (GNI) method.

This work is structured into: Section 2 surveys existing indoor localization studies. Next, Section 3 describes the dataset used, preprocessing, data augmentation, and the proposed AE-CNN model. The experimental findings, the performance analysis, and the discussion of the results are examined in Section 4, while the final segment, Section 5 presents the conclusion and future directions of this study.

2. Related works

Research papers have discussed the challenges in indoor localization for wireless sensor networks, focusing on predicting the exact position of an object and minimizing errors using various localization approaches, including both machine learning and deep learning approaches. This section provides a summary of current research. Munadhil *et al.* [11] introduced a localization framework that uses a sensor network with a backpropagation-based artificial neural network (BP-ANN), which was implemented for real-time location detection and estimation of an individual suffering from Alzheimer's disease within an internal environment. It employs four static anchor nodes based on ZigBee XBee S2C modules and one mobile node, which is mounted to the patient. Signal strength readings (RSSI) from the anchor nodes were collected by the mobile node using a laptop installed with X-CTU software. These RSSI readings were utilized as input to an artificial neural network, which resulted in 2D spatial values (x, y) as the computed location. Tareq Alhmiedat [4] proposed a localization framework based on fingerprinting and machine learning. This system employs an affordable sensor design, creates an indoor fingerprinting dataset, and integrates four customized machine learning models: Linear Regression (LR), K-Nearest Neighbor (KNN), Decision Tree (DT), and Random Forest (RF). The best performance was achieved using the KNN technique, with a mean error of 1.4 m in location estimation quality. The study also assessed the effect of the density of fixed position points on localization accuracy, revealing better localization accuracy in denser reference point placement. In addition, three independent real RSSI fingerprint datasets were created. Real experiments tested the presented framework in challenging indoor settings with various obstructions and partitions. Wei *et al.* [12] presented an advanced fingerprinting framework that combines Gaussian-Kalman filtering with a Time-distributed Auto-Encoder and Gated Recurrent Unit (TAE-GRU) to address RSSI volatility in RFID-based indoor localization. The approach first stabilizes noisy measurements through Kalman smoothing of raw signal strengths; subsequently, it leverages information related to timestamps in unsupervised auto-encoder feature learning. Successive GRU layers then learn the dynamic signal patterns, enabling the model to learn spatial and temporal correlations adaptively. This pipeline achieves a 75.9% accuracy improvement over standard neural baselines in real-world experiments, indicating that the method can overcome the effects of multipath and intermittent interference. However, despite the improvements reported, the use of RFID infrastructure and sequential processing incurs non-negligible latency and is not directly applicable for static Wi-Fi sensor networks. Jian Ng *et al.* [13] introduced LoRa-based indoor positioning system tailored for dynamic mobility in industrial settings. The system integrates LoRa technology with a fingerprinting method that utilizes the constant motion technique for fingerprint acquisition and employs a two-layer Deep Gaussian Process Regression (DGPR) model to address the non-linear aspects of signal propagation. Testing on static and motion datasets revealed that data collection during motion yielded improved results for tracking dynamic objects. Additionally, temporal-based improvements such as Temporal Weighted RSSI Averaging and Kalman filtering was included. These strategies successfully reduce RSSI temporal fluctuations and enhance the accuracy of location calculations. Lukman Ayinla *et al.* [14] introduced an enhanced Deep Neural Network framework for multi-floor indoor target localization based on Wi-Fi fingerprinting. The authors leveraged Recursive Feature Elimination with Cross-Validation (RFECV) to identify and select the most significant features. The performance of RFECV-DNNBN was evaluated on the UJIIndoorLoc and UTSIndoorLoc datasets. The results demonstrate that the method successfully addresses several limitations observed in existing AI-based localization methods in both classification and regression. Aqeel H. *et al.* [15] proposed a combination of the latest deep learning with sparse feature selection to enhance accuracy in identifying objects in complex, cluttered areas. This method combines nearly all the conventional approaches for identifying the most effective signal processing techniques and classification algorithms. To reduce signal noise, statistical, entropy-based, and stochastic differential modeling approaches are used to identify the features. Then, the best features are chosen to fix the inputs. The Long Short-Term Memory (LSTM) neural network is then trained on the selected characteristics, achieving high accuracy in classifying locations. Despite yielding high precision, this methodology requires intensive computational resources due to various complex statistical and entropy-based models. In conclusion, although previous works have achieved promising results on RSSI-based indoor localization, none of them can generate outputs with nontrivial model complexity or massive data amounts. In contrast, the proposed AE-CNN model achieves sub-meter regression accuracy on a limited amount of data. This study adopts a lightweight and robust model tailored for complex small-scale and interference environment. The advantage of Auto-Encoder has been leveraged to create compact, denoised representations of RSSI measurements allowing the CNN stage to use these clean representations to output well-defined features. Simultaneously, an augmentation strategy expands the training set by incorporating realistic signal variations, preparing the model to do well against noisy environments, temporal fluctuations, and multipath effects.

3. Materials and methods

3.1. The utilized dataset

This paper utilized the dataset presented in Ref. [4] for both the training and testing phases. The data acquisition process was conducted at the University of Tabuk, within the laboratory of the Industrial Innovation and Robotics Center with dimensions of 21.20 × 7.60 m by using five ZigBee (XBee series 2) modules, four of which served as stationary nodes and one as a mobile coordinator node for data logging. The indoor testbed comprised several robotic systems, laboratory benches, and office equipment. This configuration presented a challenging environment due to the walls and obstacles that might either attenuate or amplify radio signals [4]. The data collection procedure involved the reference nodes sending their data to the coordinator node. Next, the coordinator node captured the RSSI values and recorded them in the dataset. The original large-scale dataset employed in Ref. [4] exhibited a high spatial density of 1.216 Reference Points (RPs) per m^2. The spatial density reflected the ratio of original measurement points to the physical dimensions of the lab, measured in Reference Points per square meters [4]. Fig. 1 shows the layout of the test bench area and the distribution of the stationary nodes.

Table 1 shows the characteristics of the localization dataset, and Fig. 2 illustrates the probability distribution for the stationary nodes.

Table 1. Dataset characteristics.

Parameter	Value
Number of stationary nodes	4
Number of mobile nodes	1
RSSI values range [min, max]	[0, 110]
Original dataset size	194 samples
Spatial density	1.216 RPs/m^2
Augmented dataset size	388 samples

3.2. The proposed system architecture

This study proposes a CNN-guided Auto-Encoder deep learning model for indoor location. Fig. 3 visualizes the general workflow of the proposed model. This process is partitioned into two main phases: offline and online phases, as presented in Fig. 3. The offline phase includes the preprocessing steps for the captured dataset to prepare it for the deep learning model. The next step is the online phase, which comprises the training and validation stages, as well as the test stage.

3.3. Data preprocessing

Preprocessing constitutes a fundamental step in preparing the data for use with deep learning algorithms. Typically, data contains numerous issues, including missing values, outliers, and a wide range of signal values. The performance of deep learning techniques can be enhanced when the features lie within normalized ranges, such as [0, 1] or [−1, 1]. The dataset is arranged in rows, where each row represents a set of RSSI readings from the fixed nodes, labeled by the location corresponding to that reading, as illustrated in Equations 1 and 2.

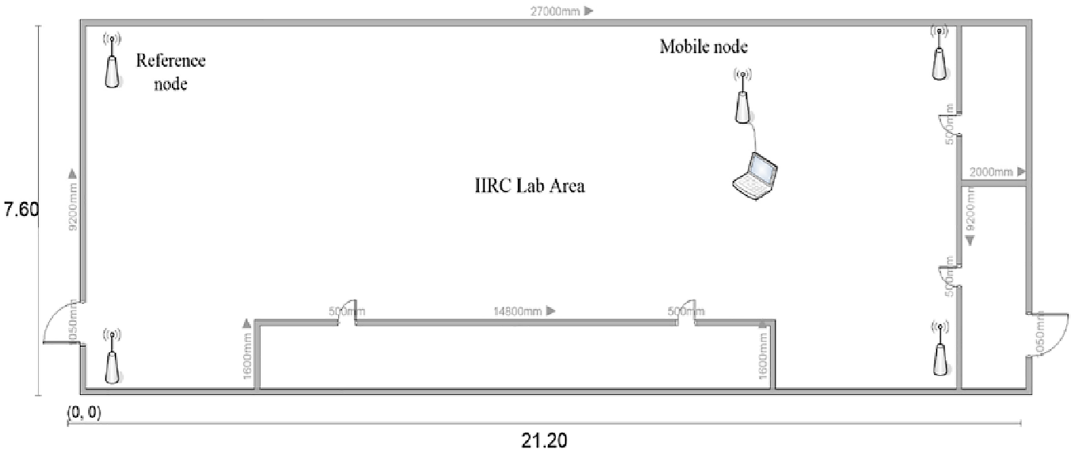


Fig. 1. Layout of the test bench area [4].

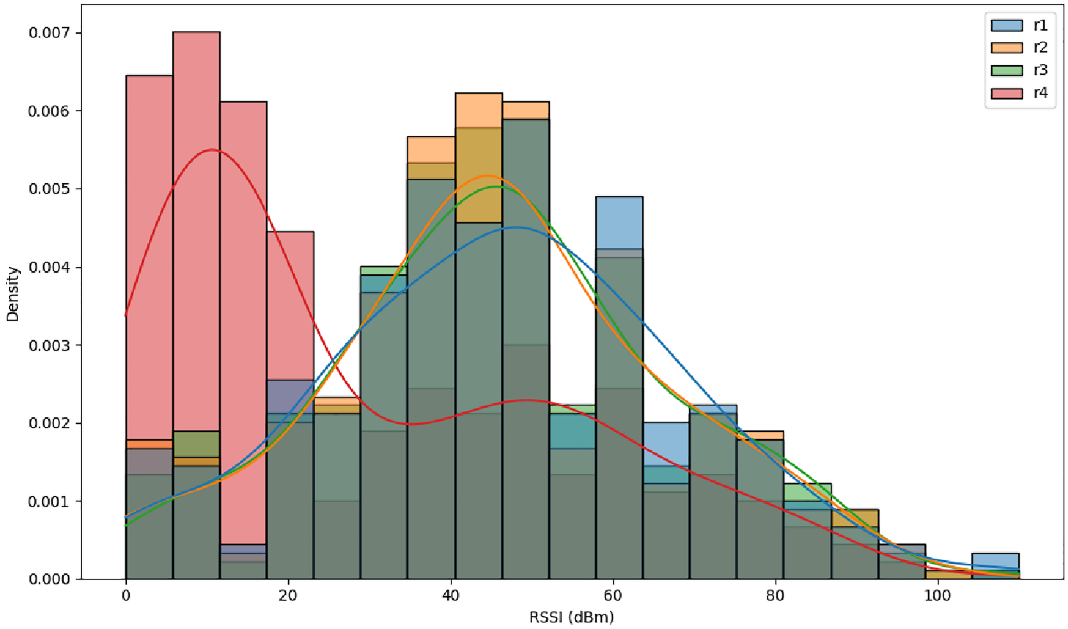


Fig. 2. RSSI measurements of the stationary nodes.

$$V_{i,j} = \left\{ v_{i,j} : v \in \mathbb{R}^{n_p \times n_r} \right\}, i = 1, 2, .., n_p ; j = 1, 2, \ldots, n_r \tag{1}$$

$$L_i = \left\{ \left(x_i, y_i \right) : x \in \mathbb{R}^{n_p}, y \in \mathbb{R}^{n_p} \right\}, i = 1, 2, .., n_p \tag{2}$$

The initial step in preprocessing the dataset involved transforming the RSSI features into a normalized form and adjusting them to conform to a standard distribution. The fitting and transformation steps are outlined in Equation 3 through 5. In the fitting step, the mean values and standard deviations for each feature in the dataset are calculated, as illustrated in Equations 3 and 4.

$$\mu_j = \left\{ \frac{1}{n_p} \sum_{i=1}^{n_p} V_{i,j} \right\}, j = 1, 2, \ldots, n_r \tag{3}$$

$$\sigma_j = \left\{ \sqrt{\frac{1}{n_p} \sum\nolimits_{i=1}^{n_p} \left(V_{i,j} - \mu_j \right)^2} \right\}, j = 1, 2, \ldots, n_r \tag{4}$$

Next, Equation 5 is applied to transform the features into a standard distribution.

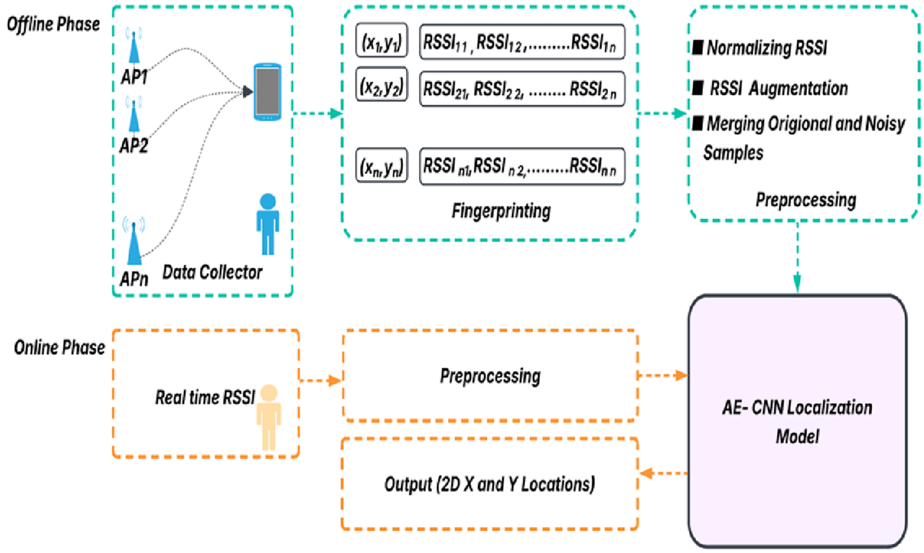


Fig. 3. System architecture of the proposed model.

$$V'_{i,j} = \frac{V_{i,j} - \mu_j}{\sigma_j} \tag{5}$$

The next step is to transform the standardized values to the range [α] = 0, [β] = 1. This normalization process is illustrated in Equations 6 and 7.

$$min_j = \left\{ \min_i V'_{i,j} \right\}, max_j = \left\{ \max_i V'_{i,j} \right\} \tag{6}$$

$$V''_{i,j} = \left\{ \alpha + \frac{\left(V'_{i,j} - min_j\right)(\beta - \alpha)}{max_j - min_j} \right\} \tag{7}$$

The final normalized dataset $V''_{i,j}$ will serve as the input for the proposed AE-CNN model. Fig. 4 shows the final distribution of $V''_{i,j}$.

3.4. The AE-CNN model

Deep learning methods are widely adopted for localization tasks. This paper proposes a model that utilizes AE-based convolutional networks as a solution to the localization problem from RSSI signals. Using Auto-Encoder in indoor localization tasks introduces several advantages for AI model performance. Wireless signals are inherently noisy due to their characteristics, such as multipath fading, reflections, environmental interference, obstacles, and the heterogeneity of the utilized devices. Auto-Encoders can reduce noise in data sourced from wireless signals because they can learn to recognize and reconstruct noiseless signal patterns. Hence, Auto-Encoders enhance signal stability, consistency of signal fingerprints, and the overall robustness of the model. Furthermore, AEs learn non-linear transformations from the captured signals and produce more informative features for the indoor localization problem. Therefore, AE utilization reduces the localization errors in real-world, noisy indoor environments. The input to the model consists of the RSSI readings from stationary nodes. The data are then processed in the encoding stage, during which the dimensionality of the input is reduced by a factor of four using scaling factors of 80, 40, 20, and 10. The output of the encoder enters a latent layer, focusing on important features with high information gain. The latent layer serves as the input for the decoding stage, which is designed to re-expand the dimensionality of the response map produced by the latent layer. During the decoding, the transformed focused features are expanded to produce a distributed, weighted response map. The size of the final layer is the same as the size of the input encoding layer. The convolutional layer follows the coding layer in the final stage of the classification process. The mean squared error (MSE) was used as a loss function to assess the performance of the training process during training. The model utilizes the ADAM (Adaptive Moment Estimation) optimizer for both forward and backward passes. The modeling process is a regression process used to estimate indoor coordinates. Table 2 shows the model training parameters, while the implementation details of the suggested AE-CNN approach are summarized in Fig. 5 and Table 3, respectively.

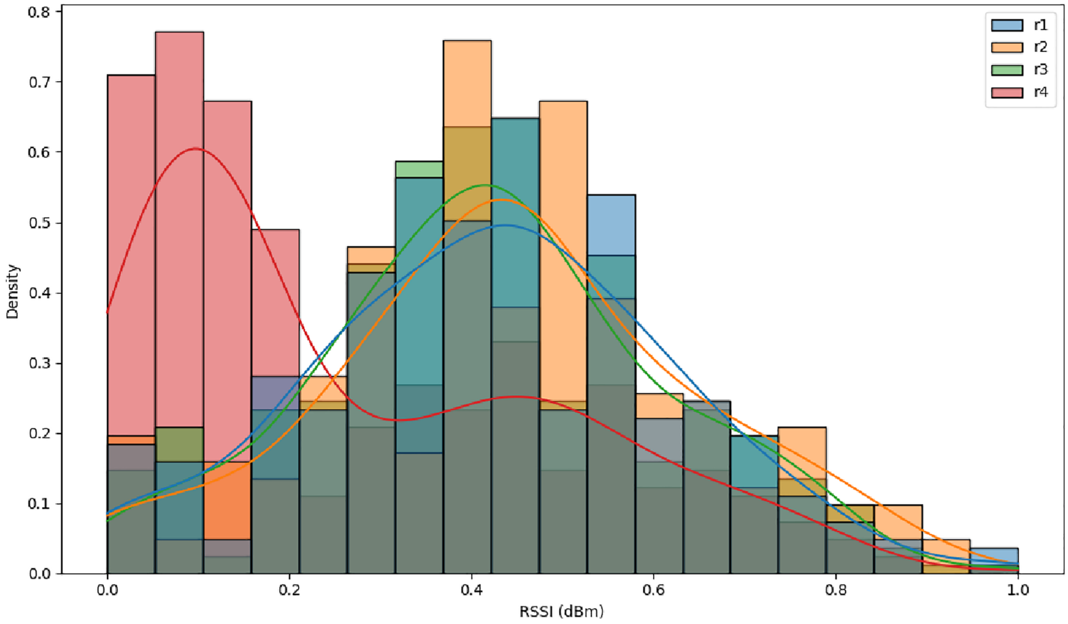


Fig. 4. Normalized RSSI of the stationary nodes.

Table 2. Parameters used for training the model.

Parameter	Value
Optimizer	ADAM
Loss function	MSE
Metrics calculated	Accuracy, MSE
Number of epochs	100
Batch size	32
Encoder activation function	ReLU
Latent layer activation function	Softmax
Decoder activation function	ReLU
CNN activation function	LeakyReLU

Table 3. Implementation of the suggested AE-CNN model.

Layer	Shape	Activation Function
Input	(,4)	-
Encoder		
Fully connected	(,320)	ReLU
Fully connected	(,160)	ReLU
Fully connected	(,80)	ReLU
Fully connected	(,40)	ReLU
Latent		
Fully connected	(,4)	Softmax
Decoder		
Fully connected	(,40)	ReLU
Fully connected	(,80)	ReLU
Fully connected	(,160)	ReLU
Fully connected	(,320)	ReLU
Dropout		
Dropout	20%	-
Expand dimensionality	(1, 320)	-
CNN		
CNN1D	(,1, 8)	ReLU
Batch normalization	(,1, 8)	-
LeakyReLU	(,1, 8)	-
Reduce dimensionality	(,8)	-
Regressor		
Fully connected	(, 2)	Linear

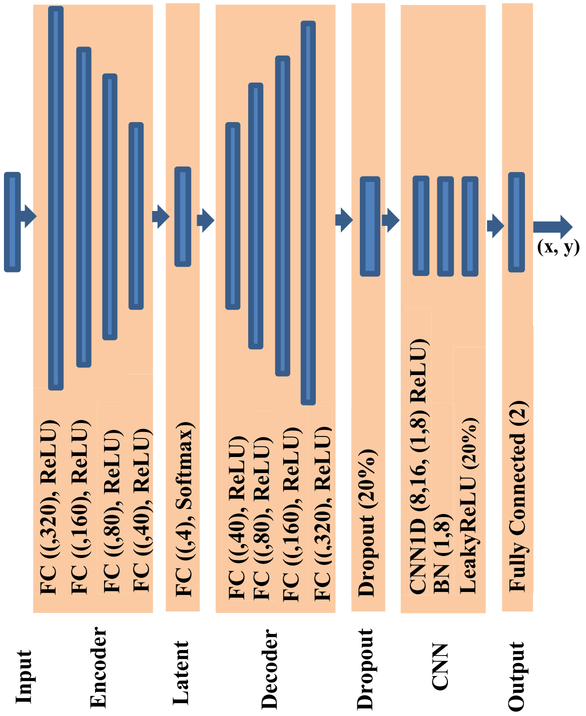


Fig. 5. AE-CNN model structure.

3.5. Model data augmentation

This paper employs three methods for data augmentation: Gaussian Noise Injection, Gaussian Mixture, and Bayesian Gaussian Mixture. The purpose of data augmentation is to maximize both the scale and variety of the training data. Given that the selected dataset is relatively small, using data augmentation will increase its size while maintaining its underlying probability distribution. The impact of these methods on model performance is detailed in the results section.

3.5.1. Gaussian noise injection model

The method employed here is to fit the data for each stationary node reading to a Gaussian normal distribution and draw one sample for each reading, thereby doubling the dataset volume. This process draws one sample from a univariate normal distribution, denoted by Equation 8, where $\mu \in \mathbb{R}$ and $\sigma > 0$ are the mean and standard deviation of the sample.

$$R \sim \mathcal{N}\left(\mu, \sigma^2\right) \tag{8}$$

The normal distribution has a probability density function (PDF), which is illustrated in Equation 9.

$$f(r;\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}}\left(-\frac{(r-\mu)^2}{2\sigma^2}\right) \tag{9}$$

This paper utilizes Gaussian noise injection into the node feature vector $r \in \mathbb{R}^d$, as shown in Equation 10.

$$\tilde{r} = r + \varepsilon, \varepsilon \sim \mathcal{N}\left(0, \sigma^2 I\right) \tag{10}$$

This approach preserves the original distribution of the stationary nodes $\{r\}$ while injecting a stochastic variable. The parameter σ represents the magnitude of noise added to the original readings.

3.5.2. Gaussian mixture model

This model is used when modeling complex and multimodal data distributions. The utilized dataset, with shape $\{r_i\}_{i=1}^{N} \subset \mathbb{R}^d$, represents the original captured readings of the stationary nodes. When fitting this data with a GMM having K components, the distribution of the transferred dataset $\tilde{r}$ will be as shown in Equation 11.

$$\tilde{r} \sim \sum_{k=1}^{K} \pi_k . \mathcal{N}(\mu_k, \Sigma_k) \tag{11}$$

This stochastic model preserves the original distribution while maintaining diversity across learnt features.

3.5.3. Bayesian gaussian mixture model

BGMM is generally utilized for its capability to incorporate uncertainty and mitigate overfitting. It is a Bayesian process; hence, it imposes priors on the mixture weights and parameters. When fitting the dataset $\{r\}$ with BGMM, the augmented samples $\{\tilde{r}\}$ are drawn from the posterior inference distribution shown in Equation 12.

$$\tilde{r} \sim \sum_{k=1}^{K} E[\pi_k].\mathcal{N}(E[\mu_k], E[\Sigma_k]) \tag{12}$$

BGMM introduces epistemic uncertainty to the augmented samples, generating a dataset with a data-driven structure from the original samples. Additionally, BGMM can generally maintain the uncertainty of the generated dataset.

4. Experiment and results

This section illustrates a comprehensive analysis of the performance levels achieved by the proposed model across all versions of the dataset. In this paper, four experiments were conducted to cover the original dataset and three augmentation methods. The first experiment utilizes the original dataset to evaluate the model's performance on it. The performance measurements obtained from this experiment were 97% and 0.82 m for accuracy and MSE, respectively, as illustrated in Fig. 6.

The second experiment utilizes augmented data obtained from Gaussian Noise Injection to double the dataset's volume. The trend of the experimental performance shows faster adaptation during training, yielding better performance in both accuracy and MSE with scores of 98% and 0.48 m, respectively, as depicted in Fig. 7.

The third experiment utilizes the GMM augmentation method. This experiment reveals a significant degradation in accuracy and increased proximity errors, accompanied by noticeable instability in adaptation with the training augmented dataset. The performance score for accuracy was 92%, and the MSE was 3.66 m, as illustrated in Fig. 8.

The final experiment was conducted on the augmented dataset using the BGMM method. Although the method exhibits low accuracy and high proximity errors, it demonstrates excellent stability when applied to the training dataset. The experiment scores for accuracy and MSE were 94% and 2.06 m, respectively, as presented in Fig. 9.

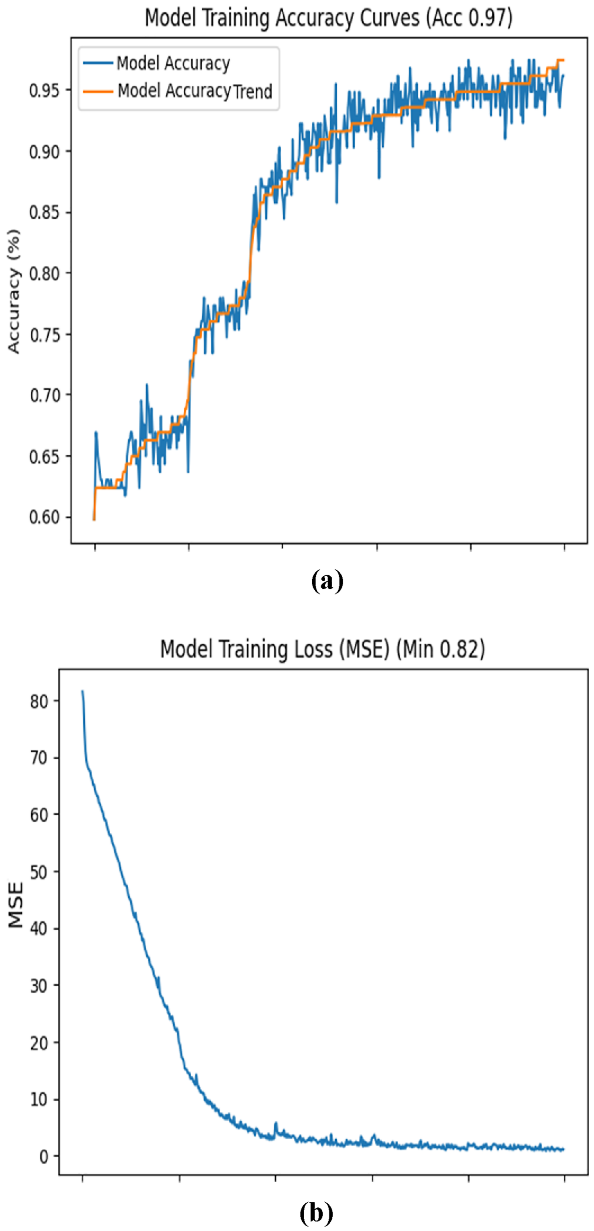
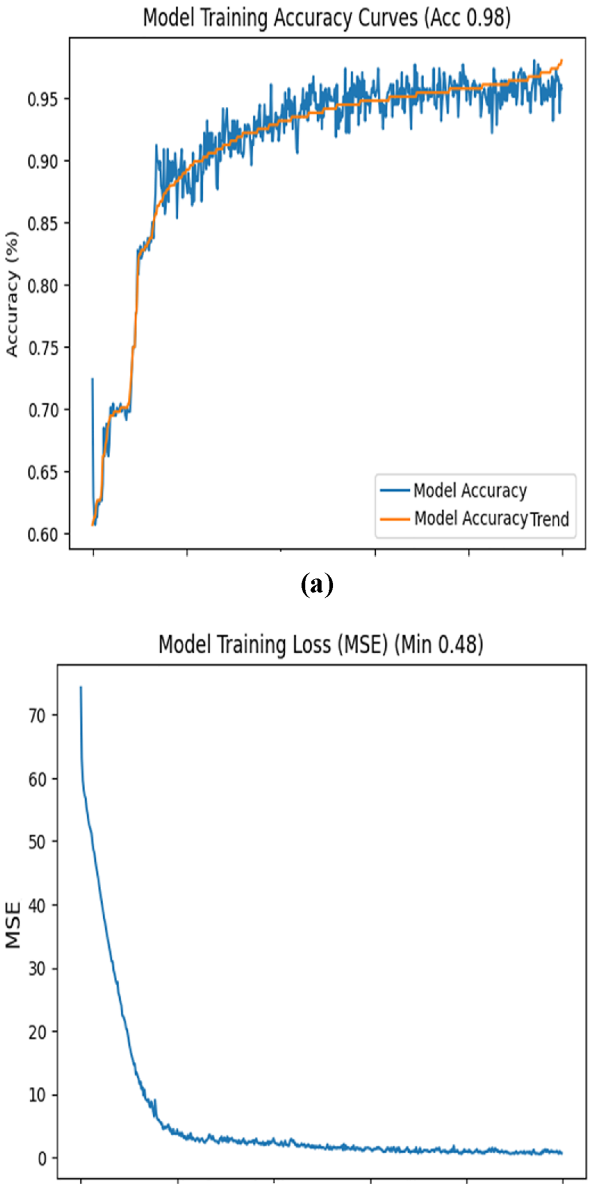


Fig. 6. Performance metrics for the proposed model using original dataset: (a) Training accuracy; (b) training MSE.

The results discussed above are listed in Table 4, which shows the effect of applying an augmentation strategy to the source data. From the table, the best accuracy and mean error of location were obtained by augmenting the dataset with the Gaussian Noise Injection method, yielding 98% accuracy and an MSE of 0.48 m.

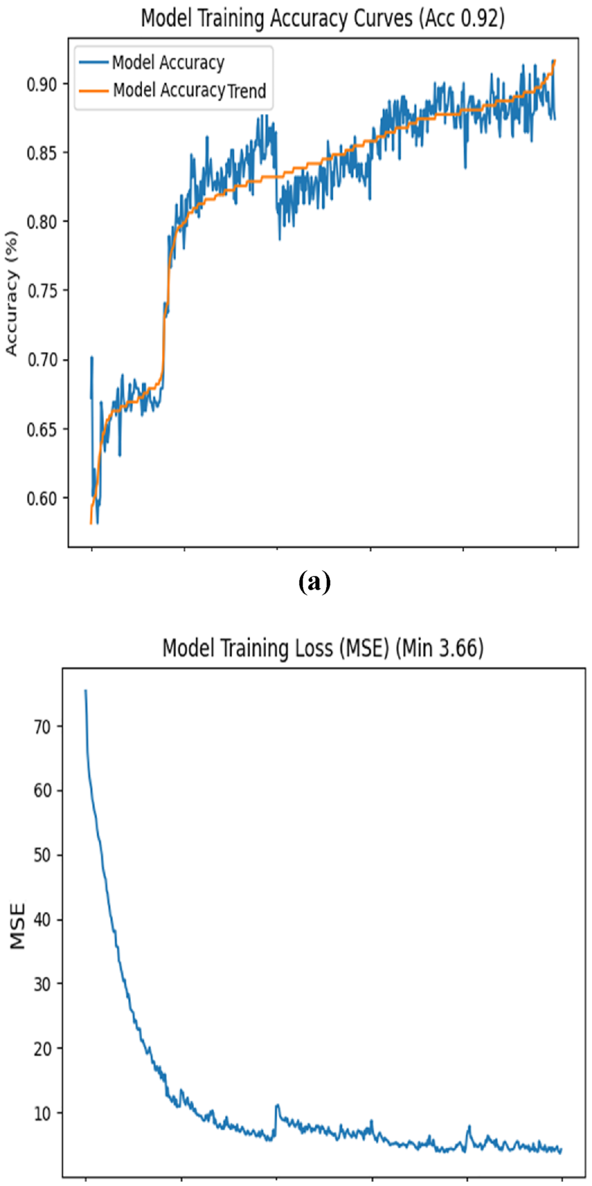
An indicative comparison of the obtained results with those from other referenced literature is detailed in Table 5. This evaluation is presented as a contextual benchmark.



(a)

(b)

Fig. 7. Performance metrics for the proposed model using Gaussian noise injection: (a) Training accuracy; (b) training MSE.



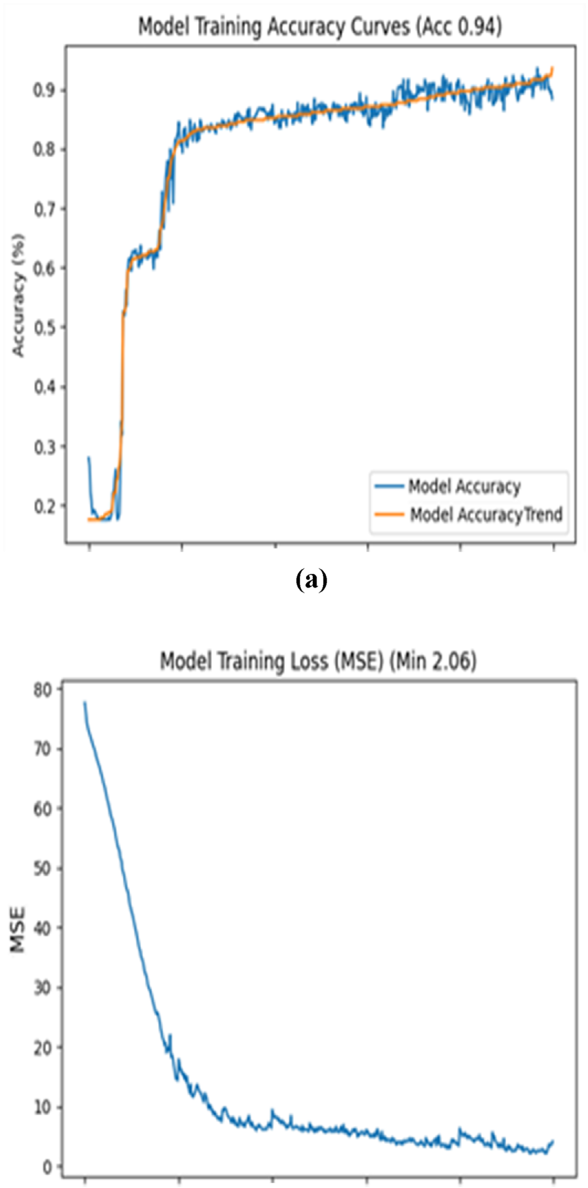
(a)

(b)

Fig. 8. Performance metrics for the proposed model using Gaussian mixture model: (a) Training accuracy; (b) training MSE.

5. Conclusion and future work

This paper demonstrates the effectiveness of implementing AE-based CNNs in solving the problem of indoor localization. The utilized dataset has a relatively small number of captured readings. This problem was addressed through the application of data augmentation techniques described in this paper. Integrating these approaches leads to a hybrid DL model that has shown promising results in comparison with other models, while remaining lightweight enough to be deployed within low-resource WSN devices. The performance of the utilized augmentation methods varies in adapting to the presented samples. The highest performance was recorded using the Gaussian Noise Injection method, which resulted in 98% accuracy and a low error of 0.48 m. Finally, although remarkable results were achieved within a specific setting, the generalizability and scalability of the suggested model



(a)

(b)

Fig. 9. Performance metrics for the proposed model using Bayesian Gaussian mixture model: (a) Training accuracy; (b) training MSE.

Table 4. Training results summary.

Method	Accuracy	MSE
Original dataset	97%	0.82 m
GNI	98%	0.48 m
GMM	92%	3.66 m
BGMM	94%	2.06 m

will be tested in larger, more complex, and multi-floor environments. Additionally, the datasets will be expanded across multiple buildings for future work.

Table 5. Indicative comparison with other literature.

The Research Work	Technology	Method	Localization Error (m)
2023 [4]	ZigBee (XBee)	KNN-based fingerprinting	1.4 m
2023 [16]	Wi-Fi	Linked-DNN	8.1 m
2024 [17]	Wi-Fi	CNN+Convolutional Auto-encoder	9.5 m
2024 [18]	Wi-Fi	Multi-output Gaussian process data augmentation feeding an RNN	8.4 m
2024 [13]	LoRa	Deep Gaussian Process Regression (DGPR)	1.9 m
2025 [19]	Wi-Fi	VGAE + MLP	7.1 m
2025 [14]	Wi-Fi	RFECV-DNNBN	5.0 m
This work	ZigBee (XBee)	AE+CNN based on Augmented RSSI	0.48 m

Ethics information

This study does not involve human participants or animals. No personal or sensitive data were collected or used in this research. The authors declare that there is no conflict of interest.

Funding sources

None declared.

Conflict of interest

The authors confirm no conflicts of interest.

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