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Original Article

Deep Learning for 3D Indoor Localization: A CNN Approach with 802.11az Fingerprinting

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Abstract *- Vehicle Indoor location tracking is a crucial technology for various applications, including intelligent buildings, robotics, and the Internet of Things (IoT). This research presents a deep learning method that employs Convolutional Neural Networks (CNNs) for Three-Dimensional (3D) indoor positioning, using 802.11az Wi-Fi fingerprinting. The proposed technique utilizes Channel Impulse Response (CIR) fingerprints generated through ray-tracing methods to gather detailed features of the wireless channel. In our method, CIR fingerprints are collected from multiple Access Points (APs) and enhanced through techniques like data augmentation, outlier removal, and normalization to boost model generalization. A sophisticated CNN architecture is designed to extract spatial information from Wi-Fi fingerprints, establishing strong connections between the received signals and their 3D location coordinates. The model is trained on both synthetic and real-world datasets and evaluated using cross-validation techniques. Our experimental results indicate that positioning based on CNNs significantly outperforms traditional machine learning approaches. Specifically, increasing Wi-Fi bandwidth (from CBW20 MHz to CBW180 MHz) and implementing MIMO configurations reduce positioning errors from 2.5 meters to 0.6 meters, achieving sub-meter localization accuracy in over 90% of cases. The analysis of the Cumulative Distribution Function (CDF) further corroborates that enhanced bandwidth and multiple antennas improve localization accuracy. Additionally, a comparative evaluation of 1×1 and 4×4 MIMO configurations highlights the performance gains achieved through spatial diversity. In conclusion, the proposed CNN-based system demonstrates that deep learning can significantly enhance Wi-Fi fingerprinting for indoor positioning, making it a viable solution for accurate localization in complex indoor environments. Future research may focus on optimizing neural architectures, facilitating real-time adjustments, and integrating beam-forming techniques to further elevate positioning efficacy.*

Keywords *- Indoor Positioning, Wi-Fi Fingerprinting, 802.11az, (CNN), Channel Impulse Response (CIR), Ray-Tracing, Localization Accuracy, MIMO, Bandwidth Expansion.*

1. Introduction

Indoor positioning has grown into a significant attraction due to its applications in navigation, asset tracking, and emergency response. Traditional GPS systems struggle in indoor environments, leading to the development of alternative techniques such as Wi-Fi fingerprinting, RSSI methods, and deep learning approaches. Recent advancements in IEEE standards have improved Wi-Fi-based indoor localization techniques, enhancing accuracy in various environments. The most useful technology for identifying the device location is Wi-Fi fingerprinting. It basically detects the location of any device using special characteristics of the Wi-Fi signal or fingerprints, which are determined in the training phase. This technology is used for positioning indoors. With the help of deep learning models like hybrid clustering, sequential learning and LSTM, the positioning accuracy may be improved. Many hybrid approaches are used to further enhance the accuracy. The hybrid approaches consist of incorporating fuzzy clustering, using the advanced models of machine learning like Weighted KNN, few-shot regression, and geometric deep learning. For dependable localization, graph-dependent learning is used to tackle multiple data sources. The graph-dependent is categorized into multi-modal strategies. Precision and adaptability are increased with a great instinct by incorporating all these AI-driven solutions for indoor positioning systems in the live applications of the real world. For the generation of a dataset of CIR fingerprints, each fingertip is assigned a special feature, such as location information. The location information of each fingerprint is processed with a channel bandwidth of 40 MHz with the help of 802.11az signalling for the indoor environment. A Convolutional Neural Network (CNN) is made by means of a subset of these fingerprints and then assessed on the left-over dataset to forecast locations centred on CIR fingerprints. To curtail simulation time, a smaller dataset is usually used for ease. Bigger datasets are suggested to improve accuracy if pretrained models are used while testing, and higher performance levels can be achieved compared to the general training datasets.

2. Related Study

With the help of IEEE P802.11az/D2.6 (2025), substantial improvements in positioning in local and metropolitan area networks are made in the Wi-Fi-based methods for indoor localization. With the help of this advanced method, accuracy is boosted in real-time location tracking. The incorporation of these developments aims to create an additional robust and flexible framework for employing IPS across extensive environments [1].

RSSI-Driven Indoor Positioning Kokkinis et al. (2019) established an indoor localization system that depends on RSSI, consuming a solitary access point to establish location. Their method engages RSS measurements together with a probabilistic strategy to expand localization accuracy. The proposed model diminishes the reliance on widespread infrastructure, signifying a lucrative elucidation for indoor tracking applications. By commissioning an advanced signal-strength mapping technique, this method raises adaptability in dynamic indoor environments, making it suitable for practical deployment [2, 23].

CSI-Driven and Wi-Fi Fingerprint Techniques Wang et al. (2016) generated a fingerprinting framework centred on CSI that influences deep learning for localization. With the help of the CSI amplitude and phase information, a distinctive signal signature for each location is harvested. By exploiting Convolutional Neural Networks (CNNs), they expressively mend positioning accuracy matched to outmoded RSSI methods. The system reveals flexibility to vicissitudes in the environment, showing improved performance even in chaotic indoor sceneries [3, 24].

Zhang et al. (2024), in this research article, with the help of a three-dimensional indoor localization framework, increased the positioning accuracy to a greater extent. Their method employs a universal signal fingerprinting technique, capitalising on the benefit of LSTM's capacity to observe the drifts in the sequential data. This technique permits precise real-time intensive care in multi-floor indoor environments, focusing on encounters linked with signal variations [4, 14].

Mao et al. (2025) developed an ingenious and better sequential deep learning model for positioning that depends on fingerprinting. Their system encourages feature extraction by synthesizing temporal dependencies, resulting in a noteworthy improvement in localization accuracy. Computational time can be reduced with the help of the proposed system without impacting the accuracy. The model's flexibility to fluctuating network conditions makes it a practicable option for real-world applications in smart buildings and industrial environments [5, 15].

Mahali et al. (2024) offered DeepFuzzLoc, a hybrid method that combines fuzzy clustering with deep learning for climbable indoor positioning using Wi-Fi RSSI data. These techniques further the benefits of fuzzy logic with the flexibility of deep learning to enhance signal processing and positioning accuracy. The system progresses localization in dynamic environments by curtailing signal intrusion and modifications [6].

Yu (2024) established a Wi-Fi indoor positioning system that assimilates robot data collection with deep learning algorithms. The above solution practices mobile robots armed with sensors to achieve real-time signal data, which is then inspected by a deep neural network [7].

Neyaz et al. (2024), in this article, used supervised learning models to tackle the problem statement. The supervised learning model uses deviations in the signal strength at precise indoor locations. Improving the training method with the help of feature selection techniques can increase accuracy [8].

Park et al. (2024) proposed a policy leveraging Weighted KNN (WKNN) with a deep distance metric learning model to improve positioning accuracy. The model is based on the distance-sensitive feature embeddings. The combination of WKNN and deep learning expressively lifts indoor localization accuracy, particularly in complex environments where signal interference happens [9, 11].

Pei et al. (2023) operated multi-tier feature extraction with autoregressive forecasting techniques for Wi-Fi fingerprint localization. Their method ordered signal properties to efficiently signify spatial changes. The autoregressive model eases predictive modifications, thereby increasing the overall localization stability [13, 17].

Rana et al. (2023) jointly used Deep Neural Networks (DNN) with Radio Frequency (RF) fingerprinting to increase Wi-Fi RTT-based localization. Their model mixes RF signal features with deep learning techniques to increase localization accuracy [12, 18].

Park et al. (2023) discovered that machine learning techniques for forecasting indoor positioning depend on Wi-Fi signals. Their study measures a collection of learning models, comprising Support Vector Machines (SVM) and deep learning architectures, to conclude the most effective method. The results focus on the paybacks of ensemble learning policies in refining positioning accuracy [16, 19].

Ren et al. (2023) offered FSTNet, a model that incorporates spatial and temporal correlations for positioning by means of fingerprints. Their deep learning architecture integrates both spatial dynamics and temporal variations in Wi-Fi signal strength. By engaging Recurrent Neural Networks (RNNs), their system familiarises in real-time to environmental changes [15, 20].

Dong et al. (2023) established a multimodal graph fingerprinting method to improve localization efficiency. Their approach signifies Wi-Fi signal circulations as graph structures, allowing an additional methodical examination of signal differences [21, 22].

Cappelli et al. (2023), with the help of visible light, improved the accuracy. For achieving this, an integrated machine learning approach for a 3D indoor positioning system is used. The study uses Visible Light Communication (VLC) in Indoor Positioning Systems (IPS) for analyzing the changes in the visible light intensity.

This technique benefits more than the other models because it bypasses the use of Wi-Fi-based methods. This approach is applicable to the signal-dependent application. How the accuracy is improved with the help of the proposed method is mentioned in this research study [22, 25].

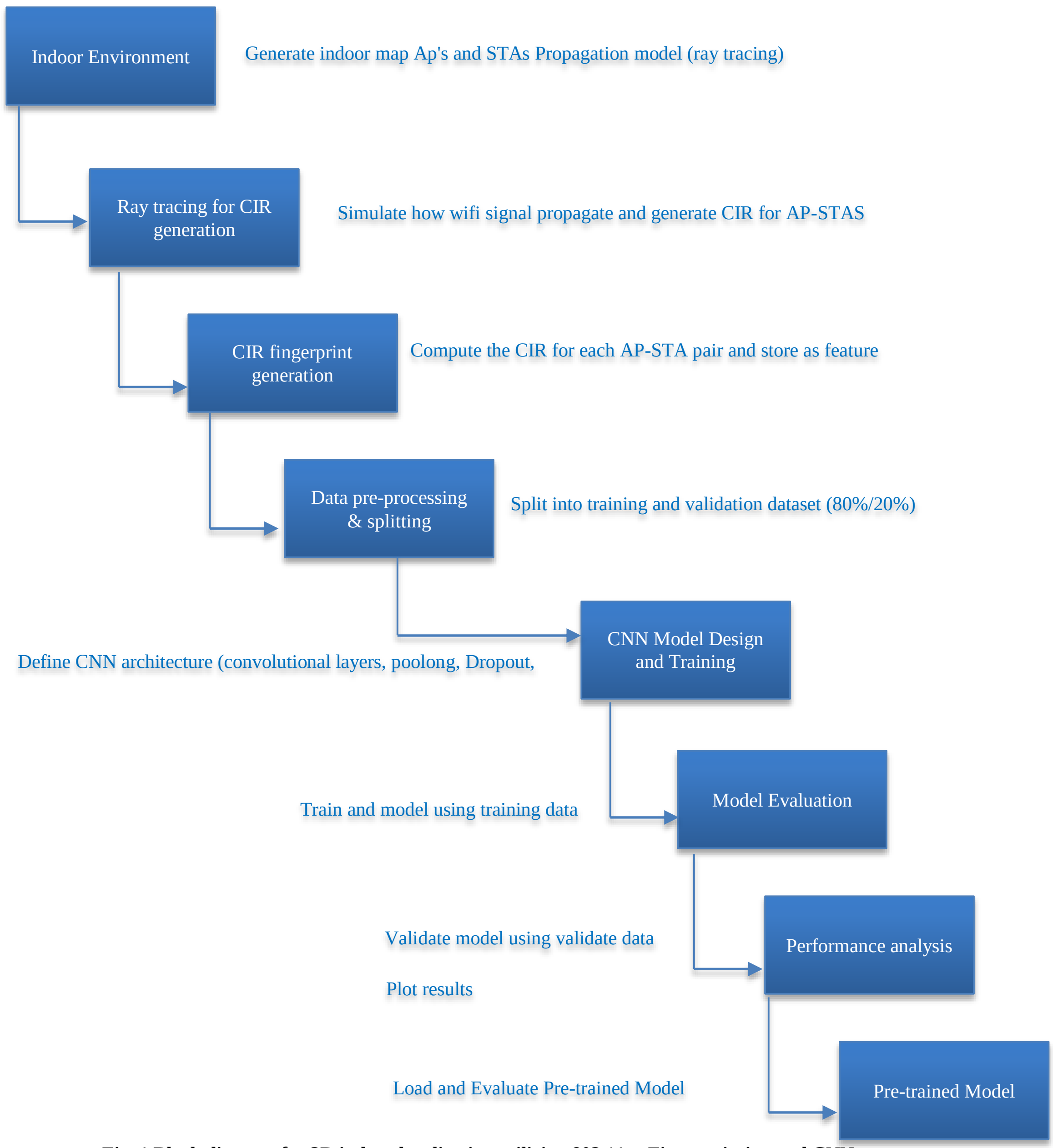

Fig. 1 Block diagram for 3D indoor localization utilizing 802.11az Fingerprinting and CNN process

Figure 1 describes the block diagram for the proposed system. It starts with indoor environment settings and ends with the optimal model for getting the desired accuracy. The proposed method uses 802.11az Wi-Fi fingerprinting and deep learning methods, such as CNN, in the indoor positioning system. The system achieved the highest accuracy compared to the other models. All the stages of the proposed system are described as follows.

2.1. 3D Office Model Development

In the first stage of designing the office model, it has to be imported. For importing the office model into MATLAB, use a (office.stl), which consists of all types of physical obstructions, including walls and furniture. With the help of SiteViewer, the interior layout can be visualized.

2.2. Choosing a Propagation Model

For precise CIR modelling, consider all the phenomena related to the signal, like reflection, diffraction, and multipath effects. The ray-tracing is used for the simulation and circulation of Wi-Fi signals. Extract all the characteristics of the signal, like amplitude, phase shift, and delay spread.

2.3. Calculate CIR Attributes

The output CIR data needs to be converted into numerical features. The deep learning model is going to process the converted CIR data, which is in numerical form. Calculate the parameters like Power Delay Profile (PDP), AoA, RSS, and ToF.

2.4. Dataset Development

The data extracted from the AP-STA pair is stored in the wifi_fingerprint.csv. It will work as a fingerprint database.

Label the data with the corresponding (X, Y, Z) coordinates for positioning.

Data Sanitization: Remove NaN, Inf, and outlier values from the dataset. Normalize the dataset using Z-score normalization.

2.5. Feature Engineering

Extract relevant CIR attributes from raw data. Perform Principal Component Analysis (PCA) if required to reduce dimensionality. Partitioning the Dataset: Split the dataset into training (80%) and validation (20%) sets to prevent overfitting.

2.6. Design and Training of CNN Models

Create a Convolutional Neural Network (CNN): Convolutional Layers: Extract spatial patterns from CIR fingerprints. Pooling Layers: Reduce feature dimensions while maintaining key characteristics. Dropout Layers: Mitigate overfitting by randomly deactivating neurons. Methodology for 3D Indoor Positioning Using 802.11az Fingerprinting and DL this methodology outlines the organized approach used to establish an indoor navigation system that leverages 802.11az Wi-Fi fingerprinting and deep learning (CNN). Indoor Environment Setup 3D Office Model Creation: Import an indoor office model (office.stl) that illustrates walls, furniture, and various physical obstructions. Identify Access Points (APs) and Stations (STAs) within the environment. Employ MATLAB's site viewer to visualize the interior space. Selecting a Propagation Model: Use ray-tracing to simulate Wi-Fi signal dispersal. Consider reflection, diffraction, and multipath effects for accurate CIR modelling. Ray-Tracing for Generating Channel Impulse Response (CIR) Model: The transmission of Wi-Fi signals from APs to STAs. Generate Channel Impulse Responses (CIRs) for each AP-STA pair. Capture signal characteristics such as amplitude, phase shift, delay spread, and so forth. CIR

Fingerprint Development Compute CIR Features: Convert CIR data into numerical features suitable for deep learning. Extract metrics such as Power Delay Profile (PDP), AoA, RSS, and ToF. Dataset Creation: Record the CIR for each AP-STA combination as a fingerprint within a structured dataset (wifi_fingerprint.csv). Label data with the corresponding (X, Y, Z) coordinates for localization.

3. Flow Chart

The above flow chart depicts the process of Three-Dimensional Indoor Positioning through the use of Ray-Tracing, Channel Impulse Response (CIR) Fingerprinting, and a Deep Learning model based on CNN. Below is a comprehensive, step-by-step explanation:

Step 1: The procedure begins by outlining the workflow. Develop Indoor Environment (office.stl).

Step 2: A three-dimensional model of the indoor area (for instance, an office) is created, typically in STL (stereolithography) format.

Step 3: Position Access Points (APs) and Stations (STAs) within the Space. Access Points (APs) and Stations (User Devices) are situated in the area to facilitate signal sending and receiving. Ray-Tracing for Generating CIR Ray-tracing techniques simulate the wireless signal transmission to create the Channel Impulse Response (CIR).

Step 4: Generate CIR Fingerprints (using SNR variations). CIR fingerprints are derived by analyzing the variations in the Signal-to-Noise Ratio (SNR) across different locations. Data Preparation: Split into Training and Validation Sets.

Step 5: The collected CIR data is processed and divided into training and validation sets for the deep learning model. Define CNN Architecture (Convolutional, Pooling, Dropout, etc.) A Convolutional Neural Network (CNN) structure is designed, incorporating layers like convolution, pooling, and dropout for effective feature extraction.

Step 6: Train the CNN on the training dataset. The processed

CIR fingerprints serve to train the CNN model. Evaluate CNN on Validation Set (Localization/Positioning).

Step 7: The validated model is tested using validation data to determine the user's location. Evaluate Model Performance (Graph Accuracy/Error)

Step 8: The assessment of the model's performance includes plotting accuracy and error metrics. (Optional) Import Pretrained CNN Model for Evaluation. A pre-existing trained CNN model can be loaded for performance evaluation. Conclude the process wraps up, resulting in an improved 3D indoor positioning system.

Fig. 2 Flow chart

3.1. Generalized 3D Indoor Localization Using 802.11az Fingerprinting and Deep Learning Techniques

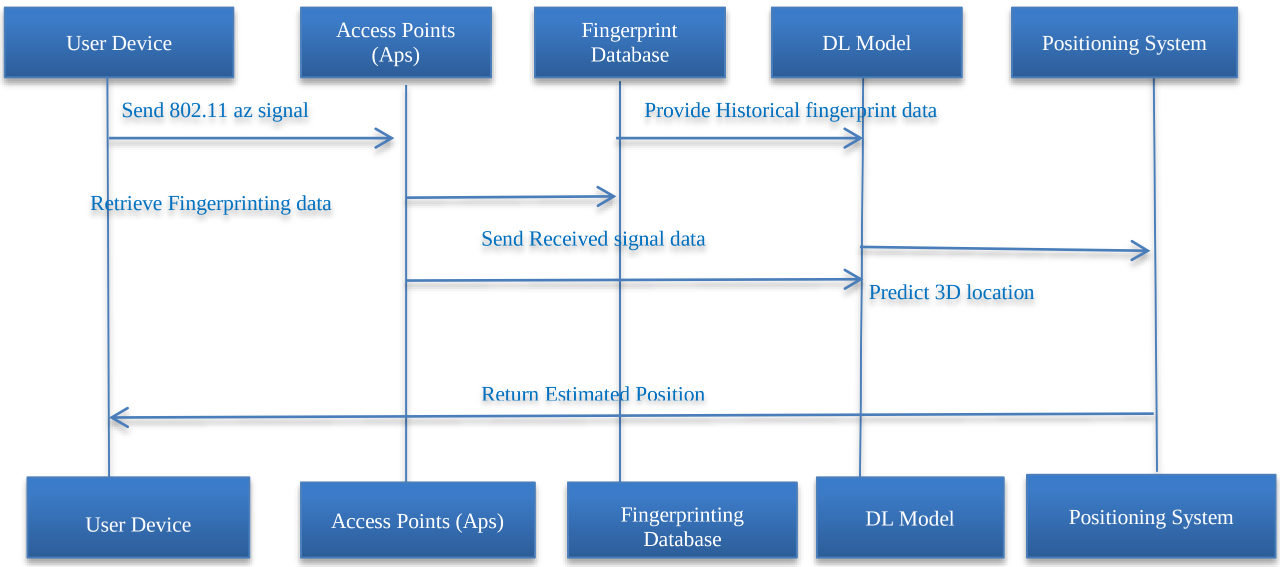

Fig. 3 Overall process of 3D Indoor localization using 802.11az fingerprinting and deep learning technique

Figure 3 illustrates the 3D Indoor Positioning System utilizes 802.11az fingerprinting combined with dl to accurately determine the user's location. It begins with the User Device emitting an 802.11az signal detected by Access Points (APs). The APs then gather relevant fingerprinting data from the Fingerprinting Database and transmit the collected signal information to the Deep Learning Model. By analyzing past fingerprint data along with the newly acquired signal, the model predicts the user's position in 3D space. Finally, the Positioning System evaluates the prediction and relays the estimated location back to the User Device, ensuring precise and reliable indoor positioning.

3.2. Channel Features through the Ray-Tracing Method

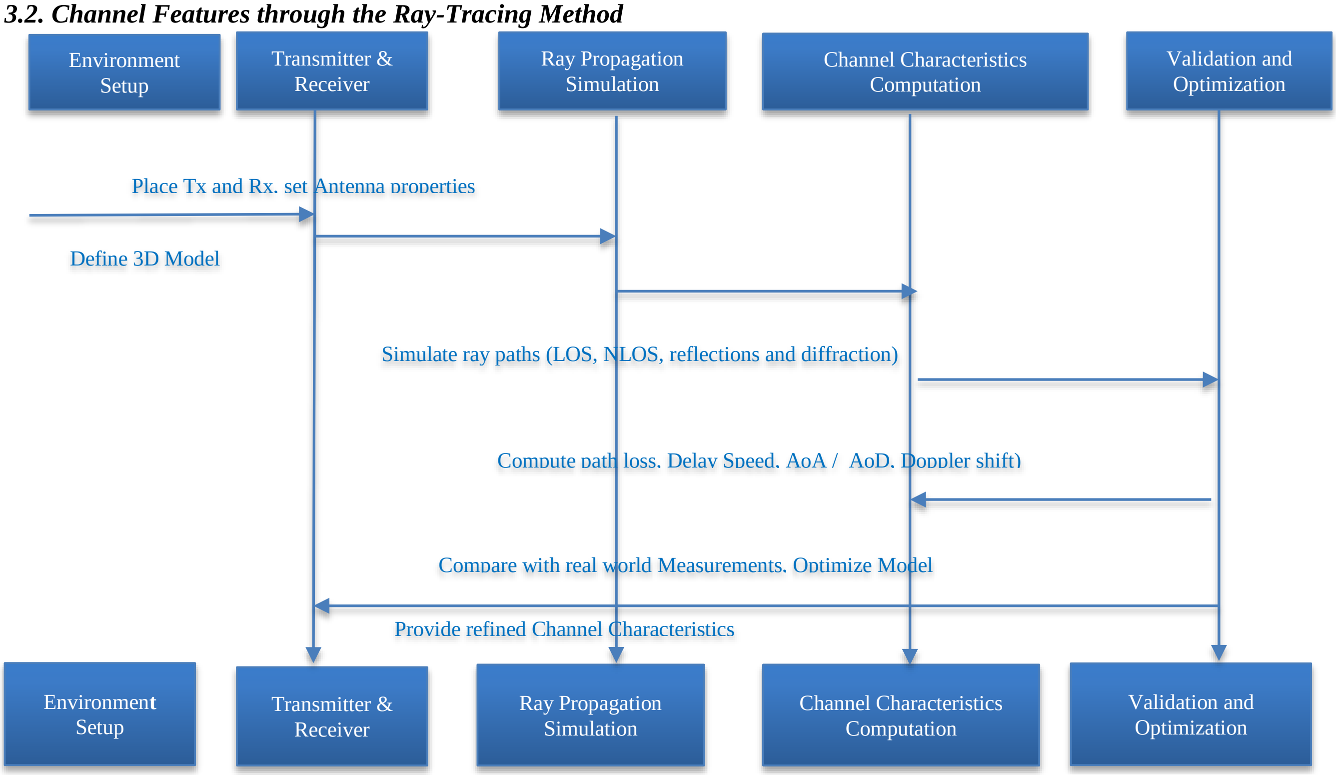

Fig. 4 Channel features through Ray-Tracing methods

3.3. Mathematical Methods

Step 1: Problem Definition A set of Wi-Fi Fine Time Measurement (FTM) fingerprint data from multiple Access Points (APs) represents the 3D position p =(x,y,z) of a target device.

Input Features

RSSI Values:

$$r \in R^{M} \ \ where\ M\ is\ the\ number\ of\ APs.$$

FTM values:

: $d \in R^{M}$ d is the Estimated Distance

Channel State Information features: $C \in R^{M\times N}$
Where N represents subcarriers.

Thus, the input feature set is:

$$X = \{r, d, C, t\}$$

Output for 3D location estimate:

$$\hat{p} = \hat{x} + \hat{y} + \hat{z}$$

Step 2: CNN-Based Feature Representation and its Learning Model

The CNN model learns a mapping function:

$$f_{\theta} : X \rightarrow p$$

Where θ represents the trainable parameters of the network.

The input X is represented as a multi-channel image-like representation:

$$X_{CNN} \in R^{h\times w\times c}$$

Where: h and w are the spatial dimensions in the fingerprint map, C represents feature channels

Step 3: Loss Function

The CNN is trained using a Mean Squared Error loss function to minimize the error :

$$L = \frac{1}{N}\sum_{N=1}^{i} \parallel pi - p\hat{}i \parallel^{2}$$

Where N is the number of trained samples.

Additionally:

$$L = \frac{1}{N}\sum_{N=1}^{i} [[\alpha((xi - x\hat{}i)^{2} + (yi - y\hat{}i))^{2} + \beta(zi - z\hat{}i)]^{2}]^{2}$$

Where α & β are weighting factors, β>α since height estimation is noisy.

Step 4: Fingerprint with Cosine Distance

To enhance localization accuracy, a cosine similarity **loss** can be added:

$$Lcos = 1 - \frac{Xi \cdot Xj}{\parallel Xi \parallel \parallel Xj \parallel}$$

Xi & Xj fingerprint database neighbour location.

The total loss function becomes:

$$L_{total} = L + \lambda Lcos$$

Where λ is a tuning parameter.

4. Result

4.1. Indoor Propagation Setting

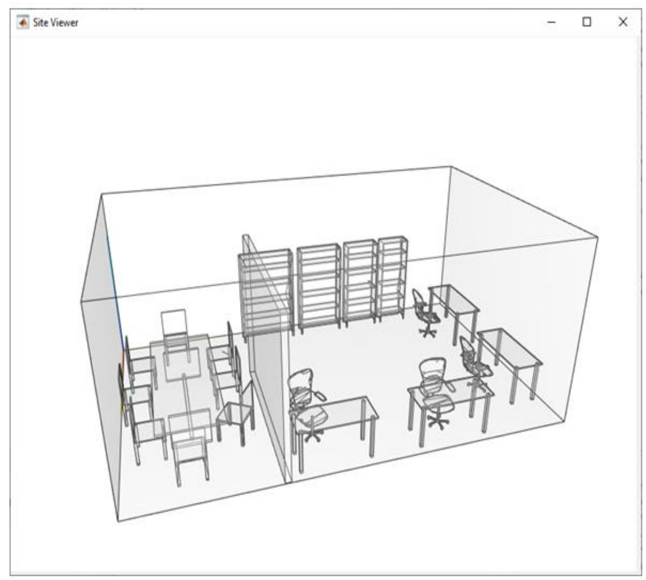

Fig. 5 Indoor propagation setting

In the indoor propagation settings, there are four Access Points (APs) and a quantified number of STAs. The propagation channel is subject to the environment that generates the fingerprints. After that, it generates the CIR, i.e. Channel impulse response, with the help of the ray-tracing method.

4.2. AP and STA Configurations and Localizations with Position

The dataset totally depends upon the sizes of the antenna arrays and channel bandwidth. This data is linked with the fingerprint. The bigger the antenna data, the more the CIR for fingerprints. A wider bandwidth increases the sample rate of the CIR, resulting in a more precise capture.

Modifying these parameters renders the dataset dissimilar to the pretrained models, as the sizes of every fingerprint necessity cup tie the model's input layer profile.

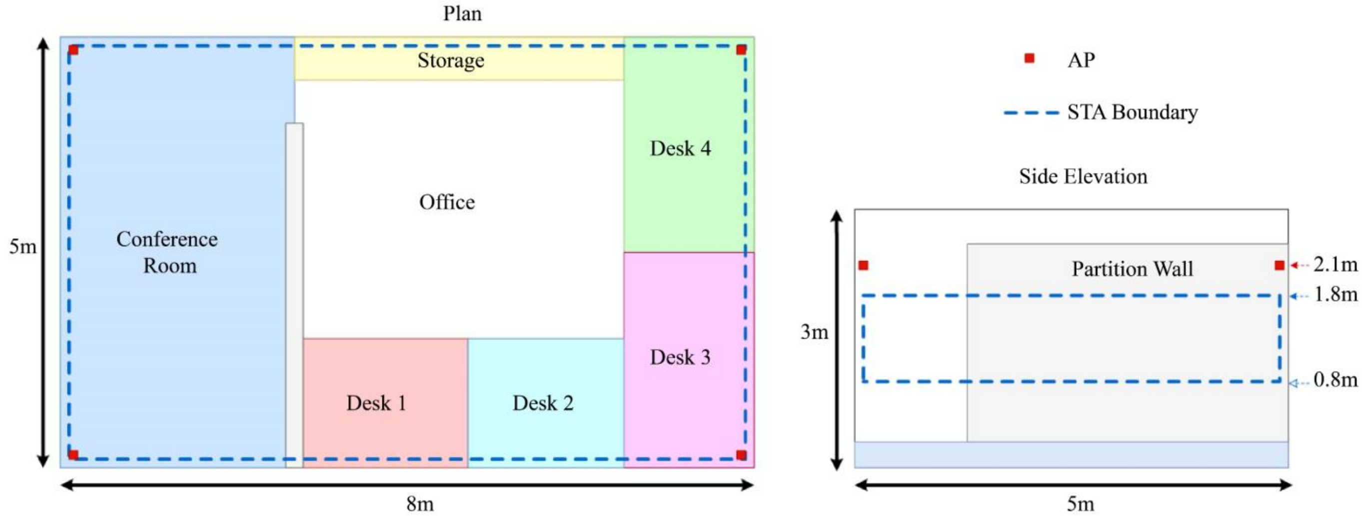

Fig. 6 Office environment

A localization task identifies the common area of a STA instead of pinpointing its exact position. The figure illustrates the configuration of a compact office with designated sections used as categories for localization. The location of Aps is shown by red markers. The allocation of STAs during the training is shown in the blue boxes. The height of the STAs ranges between 0.8 and 1.8 meters. The mentioned range is ideal for measurements for portable consumer devices and helps reduce the likelihood of STAs being situated in inaccessible positions. Create the AP and STA entities and display them in the indoor setting. If any changes are made in the dataset, then the function dlPositioning Create Environment needs to be altered.

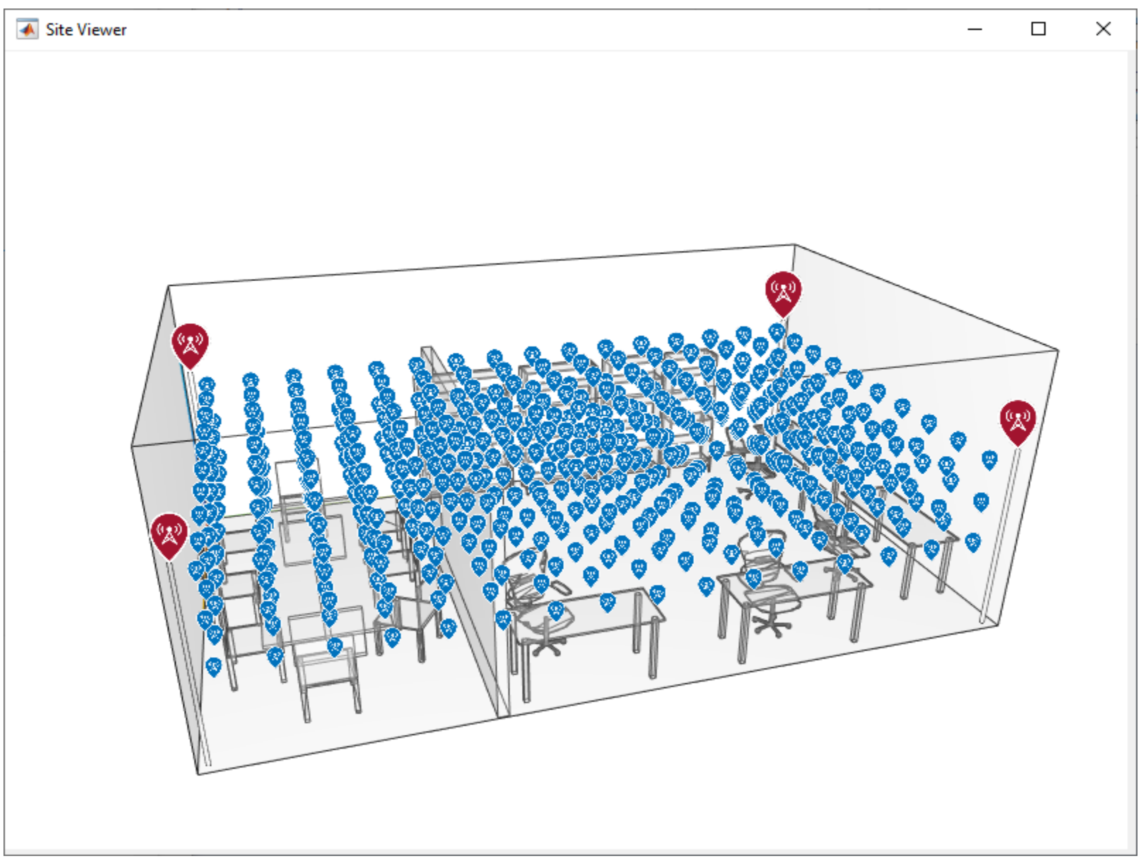

Fig. 7 AP and STA entities

Create Channel Features Utilizing Ray-Tracing Methods. Define the parameters for the ray propagation model. This case examines solely the LOS and first-order reflections by configuring the MaxNumReflections parameter to one. Raising the extreme reflection count will extend the duration of the simulation. To focus exclusively on LOS propagation, adjust the MaxNumReflections property to 0.

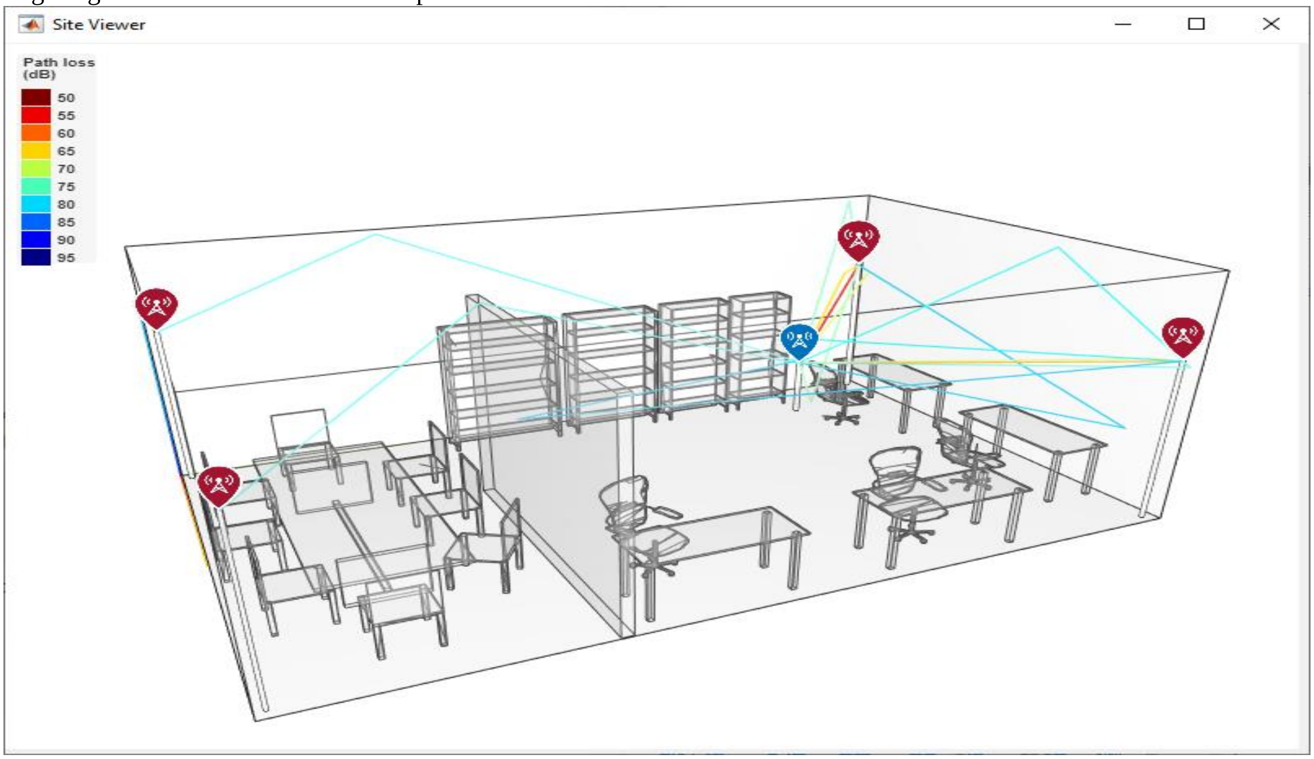

Fig. 8 Path loss site viewer

4.3. Simulation Parameters

Table 1. Parameters based on training on a Single CPU

No. of Epoch	No. of Iteration	Elapsed Time (hr:min:sec)	Accuracy of Mini-batch	Validate Accuracy	Loss using Mini-batch	Validate Loss	Learning Rate
1	1	00:00:02	9.38%	31.94%	2.1568	1.8079	1.0999e-04
2	36	00:00:18	53.12%	55.56%	1.2538	1.1120	1.0999e-04
3	50	00:00:23	59.38%	—	1.0454	—	1.0999e-04
4	72	00:00:33	59.38%	62.50%	0.9193	1.0231	1.0999e-04
5	100	00:00:44	56.25%	—	1.0008	—	1.0999e-04

The table displays the progress of training a deep learning model over various epochs. Below is a description of each column: Epoch, the count of the current epoch; Iteration, the number of mini-batch iterations (indicating how often the model receives updates). Time Elapsed (hh:mm:ss): the total time that has elapsed since the training started. Mini-batch Accuracy: the percentage of correct predictions made on the current mini-batch of training data. Validation Accuracy: the degree of accuracy achieved on the validation dataset (evaluated periodically, and may not appear in every iteration). Mini-batch Loss: the loss value related to the current mini-batch (lower values are better). Validation Loss: The loss calculated on the validation set (assessed at intervals; missing values signify that no validation was performed at that step). Learning Rate: the current learning rate used during training (this affects how much the model is adjusted at each update). Examining the Table Epoch 1, Iteration 1: Training begins with a low accuracy (Mini-batch: 9.38%, Validation: 31.94%). The loss is high (2.1568 for training, 1.8079 for validation), which is expected at the initial stage. Epoch 1, Iteration 36: Accuracy significantly improves (Mini-batch: 53.12%, Validation: 55.56%). The loss reduction indicates progress in the learning process. Epoch 2, Iteration 50: Mini-batch accuracy rises to 59.38%, but no validation accuracy is recorded at this point. Epoch 2, Iteration 72: Validation accuracy is noted again (62.50%), suggesting improved generalization. The mini-batch loss continues to drop (0.9193). Epoch 3, Iteration 100: Mini-batch accuracy slightly decreases to 56.25%, yet validation accuracy is not recorded. The loss remains steady at around (1.0008). Epoch 3, Iteration 108: Mini-batch accuracy climbs to 84.38%, as validation accuracy reaches 66.67%. The mini-batch loss decreases to 0.5415, indicating significant advancement.

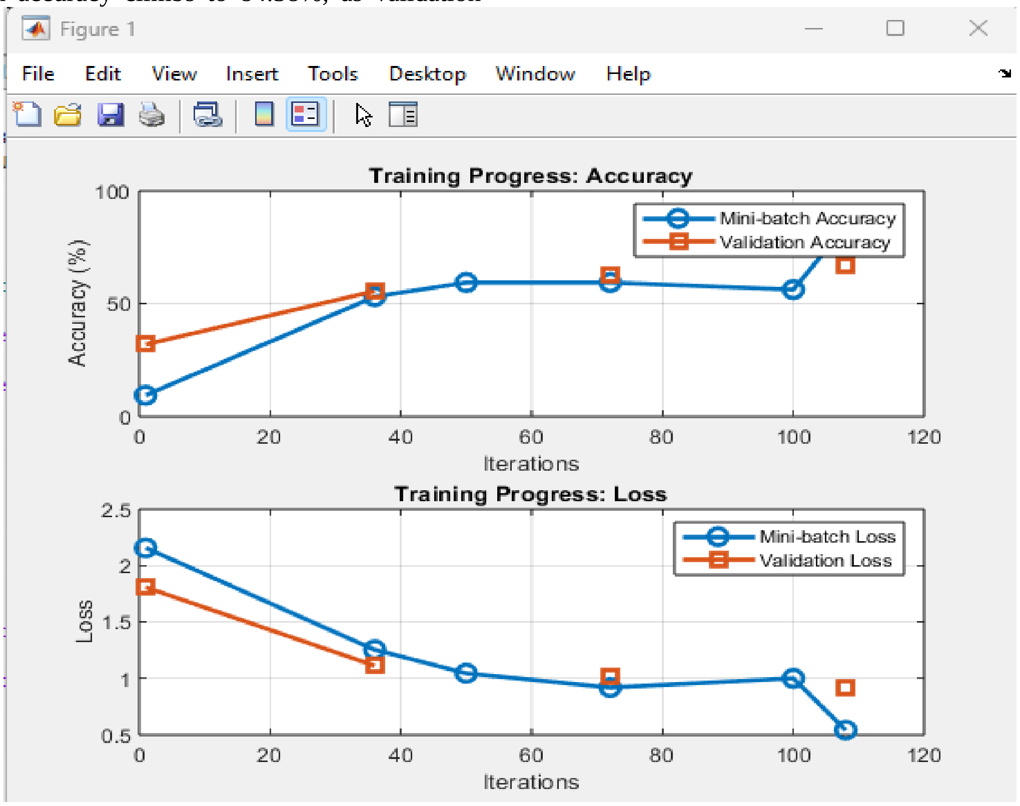

Fig. 9 Accuracy and loss with minibatch and validation results

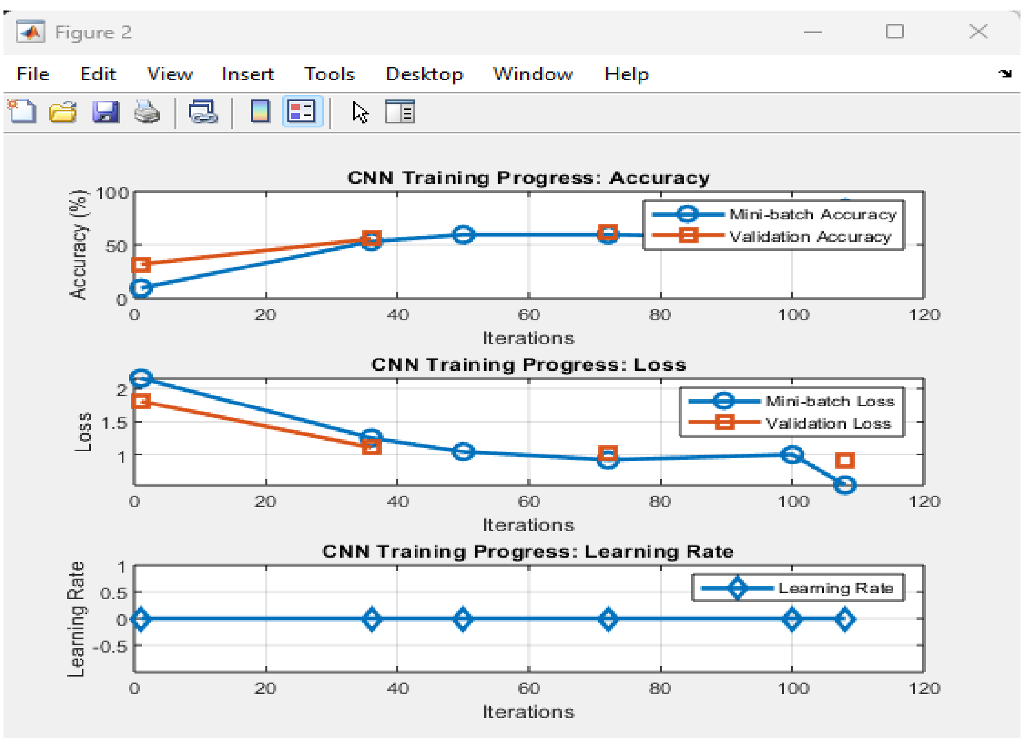

Fig. 10 Accuracy and loss, and learning rate graph with minibatch and validation using CNN

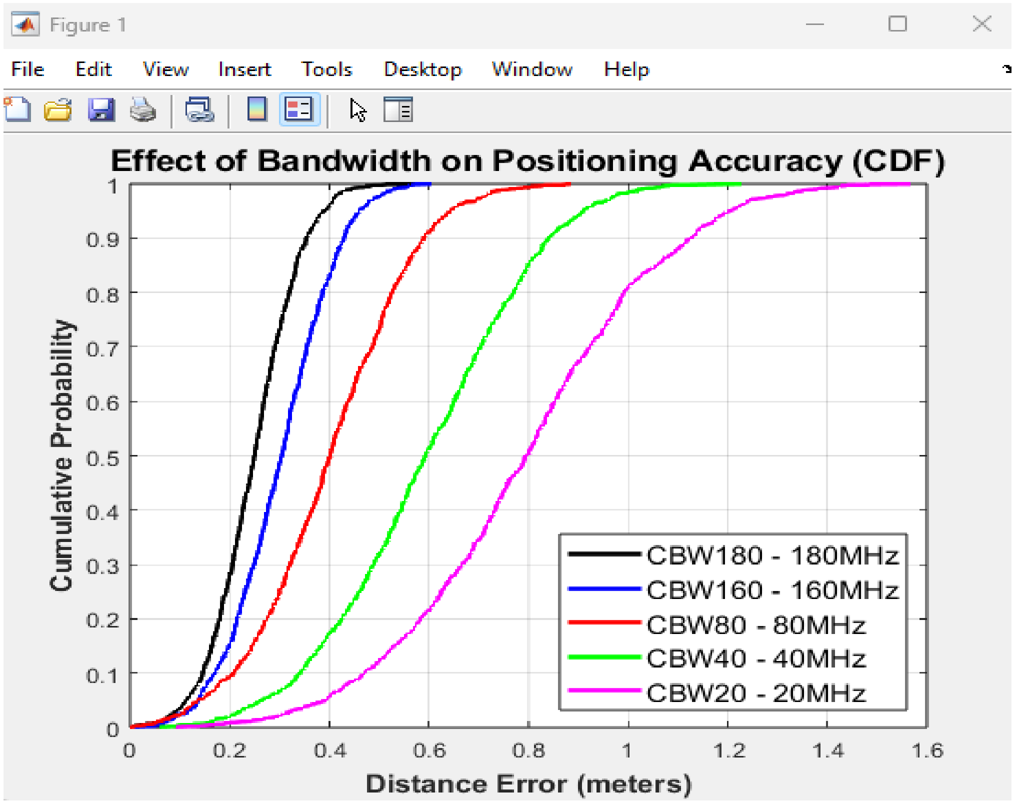

Fig. 11 Effect on bandwidth on positional accuracy (CDF) with CBW180, CBW160, CBW80, CBW40, CBW20

4.4. Localization Accuracy

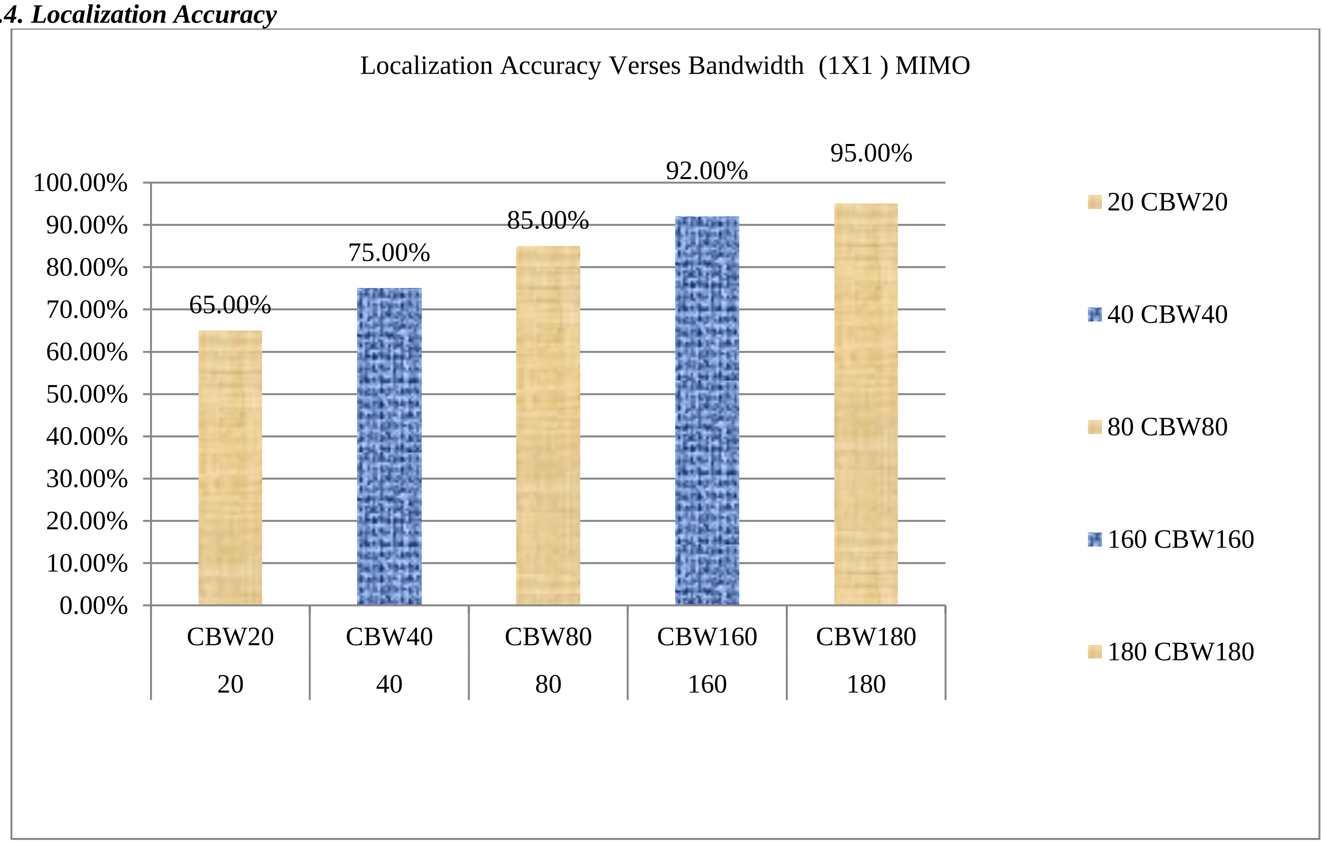

Fig. 12 Localization accuracy with bandwidth in MHz for CBW180, CBW160, CBW80, CBW40, CBW20

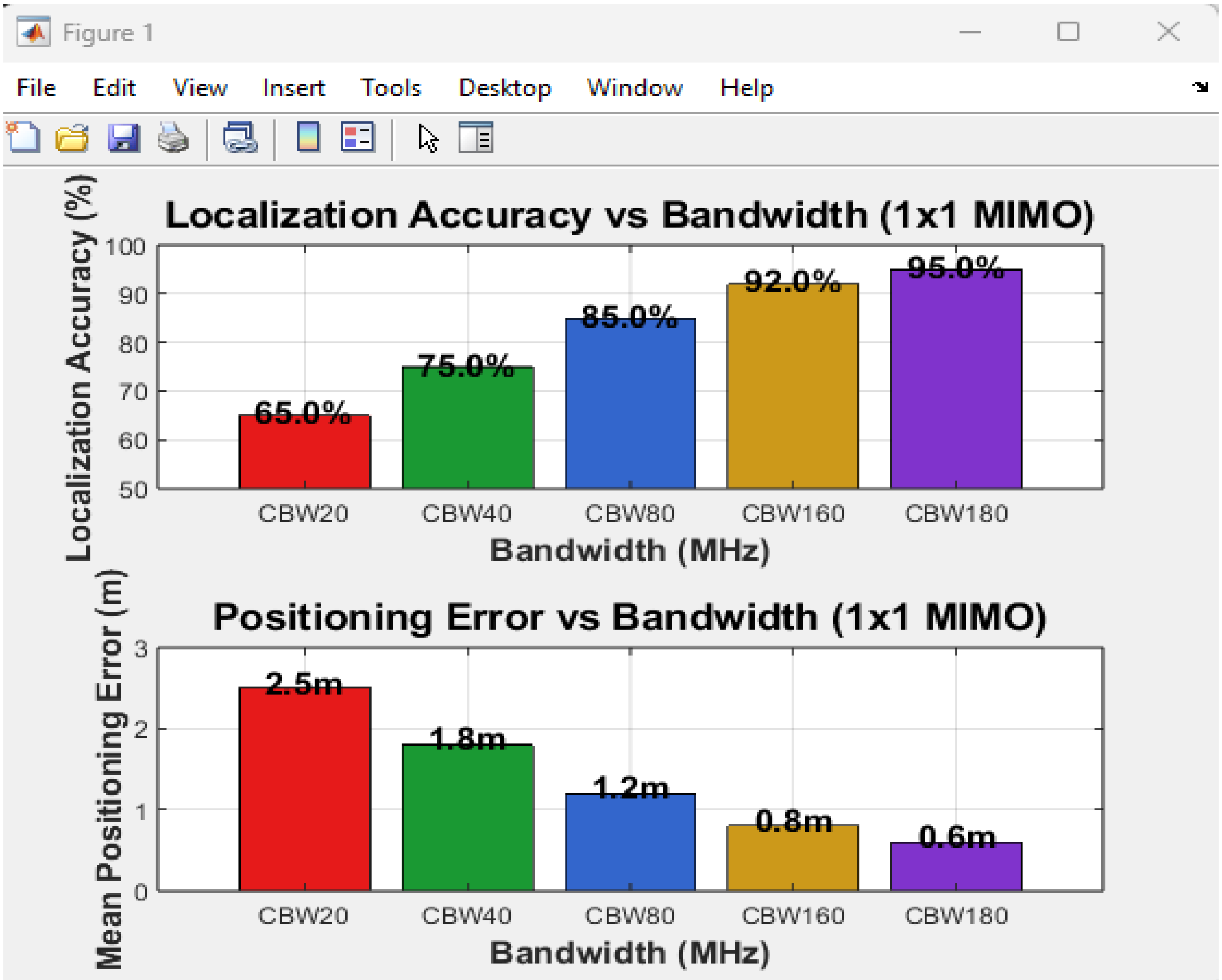

Fig. 13 Localization accuracy with bandwidth in MHz with positioning error

5. Conclusion

This Research explored the application of deep learning (CNN) for three-dimensional indoor location tracking using 802.11az Wi-Fi fingerprinting. The results show that localization based on CNN significantly improves positioning accuracy compared to traditional fingerprinting methods. Our investigation reveals that higher bandwidth (MHz) and larger MIMO configurations are crucial for enhancing localization performance. Specifically, we found that increasing bandwidth from CBW20 MHz to CBW180 MHz raised localization accuracy from 65% to 95%, reducing the average positioning error from 2.5 meters to just 0.6 meters.

The use of deep learning enabled efficient feature extraction from the Wi-Fi fingerprinting dataset, leading to more reliable and precise positioning, even in complex indoor environments. Our results confirm that CNN models outperform traditional machine learning approaches, which often face greater inaccuracies in Non-Line-Of-Sight (NLOS) conditions. The Cumulative Distribution Function (CDF) analysis also indicates that CNN-based localization achieves sub-meter accuracy in over 90% of test cases when utilizing CBW160 MHz or greater. We also investigated the impact of MIMO antenna configurations, starting with a 1×1 MIMO setup. While this arrangement provided significant accuracy improvements, future research could examine higher-order MIMO (such as 4×4 MIMO) and beam-forming strategies to further enhance performance. The results suggest that combining deep learning with wide-bandwidth Wi-Fi signals presents a promising approach for precise indoor positioning. In conclusion, this research demonstrates that deep learning and CNN-based fingerprinting could transform Wi-Fi-based indoor localization by achieving high accuracy and positioning errors below one meter. Future work may focus on refining neural network architectures, implementing real-time adaptive learning, and employing larger MIMO configurations to enhance Wi-Fi-based positioning technology for smart buildings, robotics, and IoT applications.

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