

## FINGERPRINTING BASED INDOOR LOCALIZATION: A DEEP LEARNING APPROACH

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**Abstract:** Achieving accurate indoor localization is of paramount importance for numerous applications, including asset tracking, navigation, and context-aware services. In this research, we propose a design and an implementation of a deep Convolutional Neural Network (CNN) classification model for indoor localization. The model is trained and tested using a rich labeled dataset encompassing four different indoor environments sharing a common characteristic of being located on the same floor within the same building. Each environment is characterized by varying levels of clutter: highly cluttered, medium cluttered, and low cluttered open spaces. The experimental results demonstrate a remarkable increase in localization accuracy across all environments. The average accuracy achieved by the deep CNN classification model exceeds 99%. This impressive performance highlights the model's ability to effectively distinguish and classify objects in indoor environments that exhibit varying degrees of clutter. The proposed model holds great promise for applications that rely on precise indoor localization, showcasing its potential to meet the demands of real-world scenarios.

**Keywords:** deep learning, fingerprinting, indoor localization, RF signals, Convolutional Neural Networks

### 1. Introduction

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Due to the growing need for precisely locating objects in indoor environments triggered by the Internet of Things (IoT) and its usage in a wide range of domains, including industry, healthcare, and building management [1-4], indoor localization has attracted a lot of attention. Accurate localization of objects within indoor environments is crucial information for upcoming wireless networks and services. The primary objective is to forecast the user's position within limited spaces like workplaces, healthcare facilities, retail stores, and similar environments. Typically, these environments are made up of several levels, rooms, and corridors that are crowded with people, various Instruments, and walls. Consequently, wireless signals face obstacles such as blockages, attenuation, and reflections while navigating through indoor spaces. Traditional localization techniques based on the Global Positioning System (GPS) are often unreliable or ineffective indoors due to signal blockage and multipath effects [5]. Therefore, there is a growing need for robust and accurate indoor localization solutions. Indoor localization involves a two-step process: measuring localization parameters and utilizing these measurements to estimate the location. Various techniques are used to measure localization parameters, which include channel state information [6], time of arrival (ToA) [7], time-difference-of-arrival (TDoA) [8], angle of arrival [9], and received signal strength indicator (RSSI) [10]. These techniques are implemented using a variety of access technologies, such as Bluetooth, Wi-Fi, mobile networks, radio frequency identification (RFID), ultra-wideband, and Zigbee. The seamless integration of these parameters and technologies holds promise in enabling highly accurate indoor localization services [11]. Typical range-based indoor localization methods that rely on the techniques mentioned above determine the position of an object by estimating the distance between that object and a set of anchors, usually three anchors. These techniques utilize various signals or measurements to determine the range, and then the position is calculated based on these range estimates. However, those approaches suffer from a multitude of challenges including signal attenuation, signal reflection, non-line-of-sight obstacles, and poor accuracy [12]. To mitigate these challenges, the fingerprint positioning approach has emerged as a viable solution. This method relies on measuring distinct radio frequency (RF) signals received from various access points (APs) within an indoor environment and creating a database of signal patterns or fingerprints. Each fingerprint is then associated with a specific location within the indoor space. When users seek to determine their location, their device measures the RF signals emitted by nearby APs and compares them with the stored fingerprints in the database. By matching the signals, the device can estimate the user's position accurately [13-15].

Machine learning (ML) algorithms are essential in this process as they are utilized for training models that can accurately match the measured signal patterns to the corresponding locations. These algorithms analyze the received signal strengths or other characteristics extracted from the signals and learn the relationships between these features and the known positions. The training phase involves collecting a dataset of signal measurements and their corresponding ground truth locations. The machine learning algorithm then processes this dataset to create a model that can generalize and make predictions for unseen data, during the localization phase, when a user's device captures the RF signals from nearby APs. The trained machine learning model is utilized to find the closest match between the measurements and the stored fingerprints. By identifying the most accurate match, the system can estimate the user's location [16]. Various machine learning algorithms can be employed, such as k-nearest neighbors (KNN) [38], Naive Bayes [17], random forests [18], Support Vector Machines (SVM) [19]. Although conventional machine learning algorithms improve the accuracy and robustness of the fingerprinting approach in handling challenges such as signal attenuation, interference, and multipath effects [21], deep learning (DL) algorithms offer several advantages over conventional machine learning algorithms in this context. It can be applied to various tasks, including radio map construction, feature extraction, classification, regression, and predicting device locations. Compared to conventional

ML algorithms, DL algorithms can automatically learn hierarchical representations of the input data, which is particularly useful for handling complex and high-dimensional data. DL models can effectively capture intricate relationships and dependencies in the data. Deep learning is highly acknowledged for its capabilities in distributed processing and sophisticated analytical techniques, effectively handling large volumes of both labeled and unlabeled data. Furthermore, DL can reduce the effects of signal strength variations caused by signal reflections and signal loss during transmission. The latest developments in DL techniques are likely to result in enhanced performance, reduced energy consumption, and more efficient computations, making them suitable for power-constrained Internet of Things (IoT) devices [22].

The Convolutional Neural Network (CNN) is a specialized deep neural network (DNN) used for image recognition tasks. CNN's capacity to automatically recognize critical input features that have a significant impact on the correctness of the final output is one of its main advantages. This mechanism is recognized as feature learning. Before the advent of DL, feature learning used to be a costly and time-consuming task that required manual effort [23]. This paper outlines a study with a primary focus on enhancing indoor localization accuracy using a CNN-based deep learning model that can adapt to different indoor environments and generalize well to unseen data. By leveraging the capabilities of deep learning, our objective is to overcome the shortcomings of conventional localization techniques and enhance the accuracy and robustness of object positioning in indoor environments.

This paper is structured as follows. First, a summary of previous work in deep learning-based indoor localization is presented in Section 2. The methodology and the proposed CNN-based deep learning model are explained in Section 3. The experiments setup and their results are shown in Section 4. Lastly, conclusions and future work are presented in Section 5.

## 2. Related Work

Conventional fingerprinting ML-based localization methods like support vector machine (SVM), Decision trees, K-nearest neighbor (KNN), and weighted KNN require extensive tuning which can be time-consuming. As a result, they are not well-suited for large-scale indoor environments that involve the collection and processing of substantial amounts of data [16]. Consequently, researchers have explored DL-based fingerprinting approaches as a viable alternative in such scenarios. The field of indoor localization has seen the adaptation of a wide range of deep learning algorithms [23-27]. In [28], a positioning system for device localization based on recurrent neural networks (RNNs) was presented to improve performance. They used a multi-output Gaussian approach for establishing correlations between RSSI values acquired from closely positioned multiple access points. Experimental results demonstrated that their RNN system achieved 100% accuracy in classifying buildings and 94.20% accuracy in identifying floors, respectively. An indoor localization method based on RNN for environments with buildings and floors is presented in [29]. Consecutive predictions from the building, floor, and location are achieved by this method. Authors in this study reported exceptional accuracy rates of 100% for building classification and 95.24% for floor classification. Nevertheless, authors in [30] introduced a system called DeepLocBox (DLB) that employs a single Deep Neural Network (DNN) model to predict user positions. Through experimentation, DLB demonstrated impressive accuracy rates of 99.64% for building classification and 92.62% for floor classification. Also, various convolutional neural networks are applied in the same context. For instance, a multi-cell encoding learning (m-CEL) technique based on fingerprinting is proposed in [31] for estimating position in substantial indoor environments. Using a single forward pass network, this multi-task learning method

(m-CEL) addresses the difficulties of building and floor classification. Using m-CEL, the authors implied CNN model classified buildings and floors with an accuracy rate of 95.3%. A cutting-edge indoor localization system called CNNLoc [32] has been developed to operate in multiple buildings and across various floors. To extract distinguishing characteristics from raw RSSI fingerprints, this method uses Wi-Fi fingerprints and a stacked autoencoder. During the online phase, a convolutional neural network (CNN) is utilized to achieve remarkable accuracy. The authors of the study carried out simulations using their private dataset to validate the effectiveness of this approach. CNNLoc exhibits great performance with accuracy rates of 100% for building prediction and 95% for floor prediction. However, it is worth mentioning that the localization error of the system was measured to be 10.88 m. This relatively high positioning error, exceeding 3 m, restricts its potential for real-life use cases. To handle the challenge of Fluctuating Wi-Fi RSSI measurements over time, authors in [33] proposed a CNN-based system that effectively handles the dynamic nature of RSSI. They employed a method to construct a two-dimensional virtual representation of the radio map. 1D Wi-Fi RSSI measurements, followed by the design of a CNN architecture to process these 2D radio map inputs. Consequently, the system acquires the capacity to grasp and integrate the complex structure of an RSSI-based radio map, enabling accurate predictions. Through experimentation with an extensive database, the system achieves an impressive accuracy rate of 95.41% in predicting building IDs and floor numbers. Furthermore, the accuracy rises to 95.5% when the layer of dropouts is included. Notably, this system exhibits desirable characteristics such as rapid execution and efficient time complexity. However, the previously mentioned studies do not consider the issue of accurately positioning the user within a specific floor which presents a significantly more challenging problem. The use of deep learning in indoor localization and positioning systems is still an active area of research, and various approaches and architectures are being explored. By combining the fingerprinting method with deep learning techniques, it becomes possible to leverage the power of neural networks to extract valuable information from RF signals and achieve more accurate and reliable indoor positioning results. Our research focuses on developing a CNN architecture specifically designed for accurate indoor localization across different indoor environments. The proposed CNN model aims to extract meaningful features from input data, leveraging the spatial relationships and context information inherent in indoor environments. By combining global and local context information, our model seeks to accurately estimate indoor positions on a single floor while accommodating variations in different indoor settings.

### 3. Proposed CNN-Based Localization Model

This section presents the architecture of the proposed CNN classification model for indoor localization. The architecture is designed to effectively capture spatial features and patterns from input data to enable accurate positioning in indoor environments as described next.

The architecture of the proposed CNN model, as depicted in Figure 1, leverages the capabilities of deep learning and convolutional neural networks to automatically extract discriminative features from the specified input data. The architecture comprises two convolutional layers, each accompanied by max pooling where the pool size is 3x1 to downsample the feature maps obtained from the convolutional layers. By summarizing the information across local regions, pooling helps to retain the most salient features while reducing the computational complexity of the model [34].

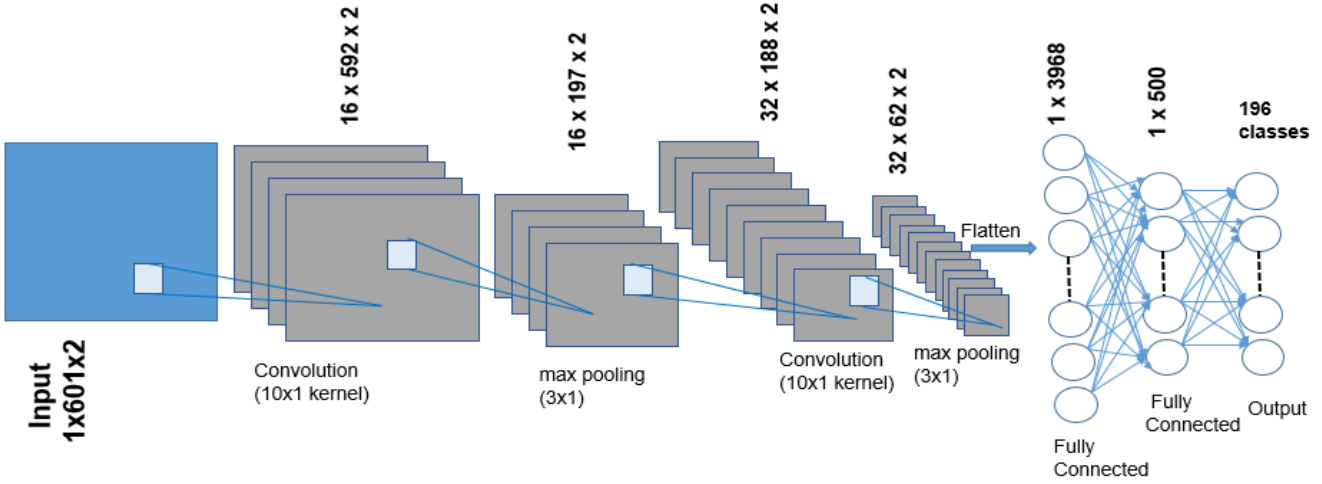


Figure 1: Proposed CNN model architecture

The first convolutional layer is comprised of 16 filters, each having a size of 10x1, through which the input data is processed. Moreover, the second convolutional layer contains 32 filters, also with a size of 10x1. To ensure network stability during training, the ReLU activation function is employed in all convolutional layers, and batch normalization is utilized [35]. After the second convolutional layer, the outputs are flattened and fed into two fully connected layers with the first layer having 3968 nodes, followed by a subsequent hidden fully connected layer with 500 nodes. The fully connected layer is activated with the ReLU activation function, and the outcome of this layer is calculated as shown in Eq. 1:

$$\mathbf{h} = \text{Relu}(\mathbf{x}\mathbf{W} + \mathbf{b}_1) \quad (1)$$

where the input vector  $\mathbf{x} \in \mathbf{R}^{(3968 \times 1)}$ , the weight matrix  $\mathbf{W} \in \mathbf{R}^{(500 \times 3968)}$ , and the bias vector  $\mathbf{b}_1 \in \mathbf{R}^{500 \times 1}$ .

To mitigate overfitting concerns and improve generalization performance, a dropout regularization technique is subsequently employed [36]. In the final step, the output is determined by utilizing a softmax layer consisting of 196 nodes, representing the total number of potential classes within the indoor environment. The softmax layer generates a set of probabilities across the 196 classes, allowing the determination of the class with the highest probability for prediction, according to Eq. 2:

$$\mathbf{z} = \text{softmax}(\mathbf{h}\mathbf{X} + \mathbf{b}_2) \quad (2)$$

where  $\mathbf{X} \in \mathbf{R}^{(196 \times 500)}$ , and the bias vector  $\mathbf{b}_2 \in \mathbf{R}^{(196 \times 1)}$ .

The model is trained using labeled data, and the errors are evaluated using the *Sparse\_categorical\_crossentropy* Loss function. The network then propagates these errors back through its layers, modifying the model parameters where the total number of parameters is 2,088,216, and gradient-based optimization methods like the Adam optimizer with a preset learning rate at 0.01 are

utilized to facilitate the parameter updates. The computation of the loss value  $L$  is calculated as specified in Eq. 3:

$$L = -\Sigma(\mathbf{u}_i * \log(\mathbf{z}_i)) \quad (3)$$

where  $\mathbf{u}_i$  denotes the true class label for the respective class,  $\mathbf{z}_i$  represents the probability prediction for the respective class after applying the softmax activation. A summary of the CNN configuration outlined in this research is presented in Table 1.

Table 2. Configuration parameters of CNN model

Model Parameter	Setting
Number of Convolutional layers	2
Kernel dimension	10x1
Pool type	Max
Pooling size	3x1
Number of fully connected layers	2

## 4. Experiments and Results

This section presents the environment setup and experimental results for the proposed CNN-based indoor localization.

### 4.1. Dataset and Experimental Configuration

To assess the performance of the proposed CNN model, a dataset obtained from [37] is employed. The dataset consists of RF signals across four distinct locations within a university campus, representing typical indoor environments. These environments consist of a highly cluttered lab, a moderately cluttered narrow corridor, a minimally cluttered lobby, and an open sports facility. To capture fine-grained variations, measurements were taken at various positions within each environment. A square grid area, partitioned into uniform cells, was meticulously arranged for the measurement scene. Each cell has 12.5 cm side length, corresponding to the wavelength at a 2.4GHz frequency, commonly associated with WiFi bands following the IEEE 802.11g standard. As a result of this configuration, a total of 196 cells were obtained. During the experimental setup, a receive antenna was systematically moved across the floor grid, precisely positioned at each cell corner. Measurements were recorded for 601 frequency points, and each sweep consisted of 10 readings. By multiplying the total grid positions, frequency points, and sweep readings, a comprehensive dataset for each environment was obtained. To ensure an equitable distribution of data for training and evaluation, the dataset for each environment is partitioned into a training set (75%) and a testing/validation set (25%). This separation enables training the model effectively using a significant subset of the data and reserves a distinct set for impartial evaluation of its performance.

### 4.2. CNN Model Training

The deep CNN classification model is trained using the training set of each indoor environment separately. In this study, the input data to the initial convolutional layer possesses a shape of a 3D matrix  $[N \ F \ C]$ , where  $N$  represents the training samples,  $F$  indicates the frequency points (set at 601), and  $C$  denotes the real as well as imaginary components of the Complex Transfer Function (CTF). The CTF represents the measured complex value of the received signal at position  $(x, y)$  relative to the transmitted signal. Hence, the CTF can be considered as the RF characteristic that represents the radio environment and is commonly referred to as an RF attribute [37]. The parameter configurations within CNN are subject to adaptation and are not rigidly predetermined since different parameter choices lead to distinct calculation outcomes. To achieve the best performance in indoor localization, various factors are considered during the continuous evaluation of the model. After conducting extensive experiments, it has been found that configuring the batch size to 32, the learning rate to 0.01, and running the training process for 20 epochs yield the optimal performance. These parameter settings have been carefully chosen, taking into account the specific characteristics of the input data and numerous iterations to ensure the CNN operates effectively for accurately classifying the indoor position (grid label). The configuration of hyper-parameters for the CNN model are outlined in Table 2.

**Table 2.** Hyper-parameter configurations for the proposed CNN model.

<b>Model Hyper parameter</b>	<b>setting</b>
Batch size	32
Dropout	0.2
Epoch number	20
Learning rate	0.01

### 4.3 Performance Evaluation

The performance evaluation of the implemented CNN deep model was conducted through four separate experiments, where the CNN model was trained and tested on datasets specific to each of the four distinct indoor settings within the same floor: highly cluttered lab, medium cluttered narrow corridor, low cluttered lobby, and open sports facility. For each experiment, the assessment metrics included average testing accuracy, precision, recall, and F-score. Where the accuracy is determined by dividing the total number of samples ( $N$ ) by the sum of true positives ( $TP$ ) and true negatives ( $TN$ ):

$$Accuracy = TP + TN / N \tag{4}$$

And the ratio of true positives ( $TP$ ) to the total of true positives and false positives ( $FP$ ) is used to calculate precision:

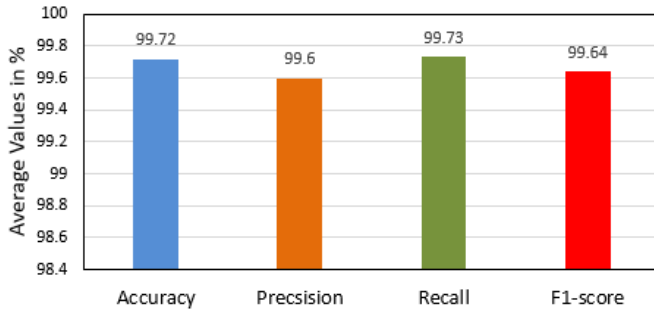
$$Precision = TP / (TP + FP) \tag{5}$$

Recall is determined by dividing the number of true positives ( $TP$ ) by the sum of true positives and false negatives ( $FN$ ):

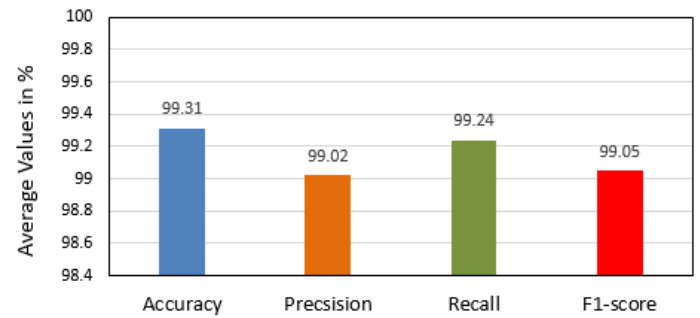
$$Recall = TP / (TP + FN) \tag{6}$$

Finally, the F-score serves as an assessment of a test accuracy, representing the harmonic mean of precision and recall. It can be calculated using the following formula:

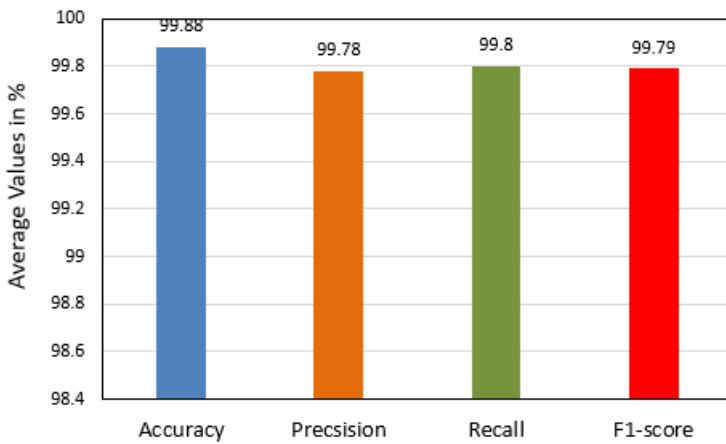
$$F - score = 2 * ((Precision * Recall) / (Precision + Recall)) \quad (7)$$



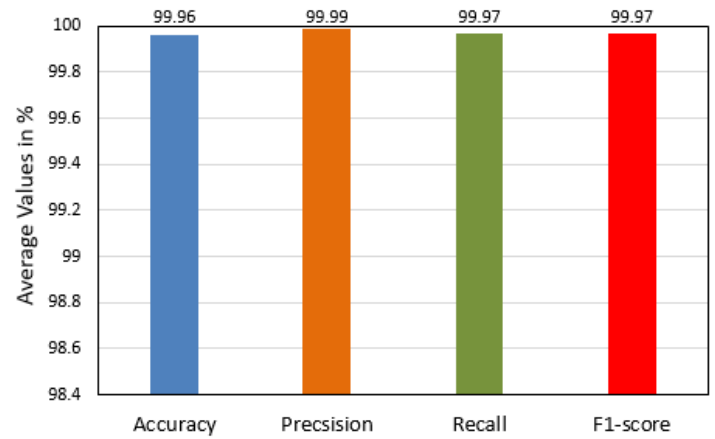
(a) Highly cluttered Lab



(b) Medium cluttered narrow Corridor



(c) Low cluttered Main lobby



(d) Open space Sports facility

Figure 2: Performance evaluation results

As shown in Figure 2(a), the model achieves an accuracy of 99.72% with precision, recall, and F1-score values above 99.6%, in the highly cluttered laboratory environment. This high accuracy can be attributed to the model ability to capture and learn intricate patterns in the RF signals. The laboratory environment typically contains a significant amount of equipment and objects that can cause signal interference and clutter. However, the model deep architecture allows it to effectively extract relevant features and distinguish between different RF signal patterns, resulting in accurate location classification. Respectively as shown in Figure 2(b), in the moderately cluttered narrow corridor environment, the model achieved an average accuracy of 99.31%. While it is slightly lower than the laboratory environment, the model still demonstrates excellent performance. The corridor environment presents unique challenges due to its limited space and potential signal reflections. The presence of walls and other obstructions can cause signal degradation and interfere with accurate location classification. Despite these challenges, the model is able to capture spatial information and patterns in the RF signals and achieve a high level of precision, recall, and F1-score values around 99%. Also, as presented in Figure 2(c) the minimally cluttered lobby environment yielded slightly higher accuracy than lab and corridor with an average accuracy of 99.88%, among the tested environments. The absence of significant clutter and the relatively open space in the lobby make it easier for the model to distinguish between different locations based on RF signals. The high precision, recall, and F1-score in



this environment indicate the model ability to accurately classify locations even in less complex settings. The open nature of the lobby allows for better signal propagation and minimal interference, contributing to the model’s exceptional performance. Similarly, it can be observed from Figure 2(d) that the open sports facility yields the highest accuracy of 99.96% among all the tested environments. The spacious and unobstructed nature of the sports facility provides optimal signal propagation, resulting in minimal signal degradation and interference. The model's ability to extract fine-grained details from the RF signals allows it to accurately classify locations in this environment. The high precision, recall, and F1-score further emphasize the model's effectiveness in handling open spaces and accurately differentiating between different RF signal patterns. These results of the performance evaluation clearly indicate the robustness and accuracy of the implemented CNN deep learning model across all four indoor environments. The high accuracy scores and balanced precision, recall, and F-score values demonstrate the model's ability to effectively classify and localize objects in highly, medium, and low cluttered, and also open space settings.

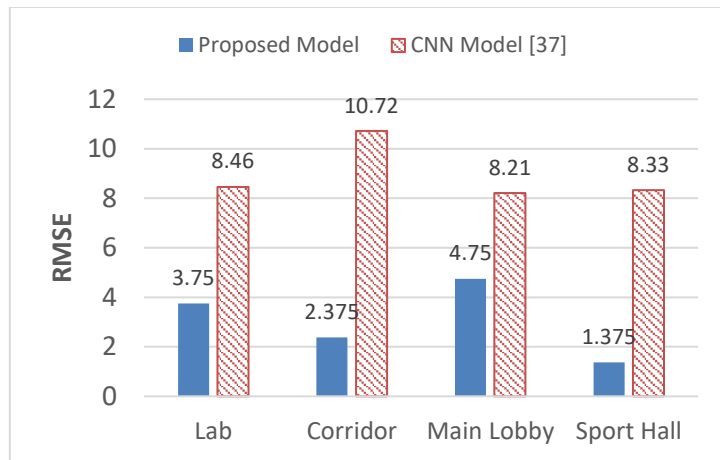


Figure 3: Comparison of RMSE obtained by the proposed CNN model and the CNN model proposed in [37]

**4.4 Comparative Evaluation**

AlHajri *et. al.* [37] proposed and evaluated a CNN model for indoor localization using the dataset used in this paper. They measured the model performance using the estimated position error (RMSE) which is calculated as follows:

$$RMSE = \left[ \frac{1}{n} \sum_{i=1}^n (\bar{x}_i - x_i)^2 + (\bar{y}_i - y_i)^2 \right]^{1/2} \tag{8}$$

where  $(x, y)$  are the true position and  $(\bar{x}, \bar{y})$  are the predicted position. Figure 3 compares the RMSE obtained by our developed model and the model proposed in [37]. It is noted that the proposed model can achieve lower RMSE over all tested environments with a max error of only 4.75 m. These promising results validate the suitability of the proposed CNN deep learning model for indoor localization, highlighting its potential to be utilized in real-world applications requiring precise object positioning within diverse indoor environments.

**5. Conclusion And Future Work**

In this paper, a CNN-based deep learning model for indoor localization is proposed and evaluated. The model is trained and tested using a labeled dataset encompassing four different indoor environments of varying clutter levels. The experimental results demonstrated exceptional performance across these various indoor environments. The analysis of individual environments revealed interesting insights where the implemented CNN model consistently achieved high accuracy, with values exceeding 99%. Additionally, the model demonstrated outstanding precision, recall, and F-score results. The results highlight the robustness and generalization capabilities of the CNN model, as it performed well across different clutter levels and diverse indoor environments.

As future work, the challenge of enhancing localization accuracy for limited training data environments will be addressed by exploring the application of deep transfer learning strategies, where knowledge can be transferred from rich training data environment. Transfer learning enables leveraging the knowledge gained from a large and richly labeled dataset in the source domain to improve the performance of the model in the target domain. This will open new possibilities for accurate indoor positioning and contribute to the development of practical solutions for a wide range of indoor applications.

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