# Enhancing Signal Coverage and Performance by Optimization of Router Placement Using Deep Learning Model

**Master of Science**

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# Enhancing Signal Coverage and Performance by Optimization of Router Placement Using Deep Learning Model

*A thesis submitted in partial fulfillment of the requirements for the award of the degree of*

**M.Sc.**
in
**Data Science**

by

**Vinod Kumar**
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under the guidance of

**Dr. Deepak Kumar Singh** **Dr. Madhurima Datta**

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*I*
*want to dedicate*
*my supervisor (Dr. Deepak Kumar Singh), for his invaluable guidance, my family, for their endless love and support, Dr. Manoj Kumar and Sourav Raj (Data Scientist at Jio Platform Limited), for their encouragement and inspiration throughout this research journey.*

# AUTHORSHIP

I, **Vinod Kumar**, declare that this thesis titled, "**Enhancing Signal Coverage and Performance by Optimization of Router Placement Using Deep Learning Model**" and the work done in it is my own. I confirm that:

- This research was conducted entirely during my candidature for the Master of Science degree at the Indian Institute of Information Technology, Lucknow.
- I have appropriately cited all published works that I consulted during the course of this study.
- All referenced sources are clearly indicated wherever citations appear in the thesis.
- Except for the cited materials, the content presented in this thesis is entirely my own original work.
- I have duly acknowledged all significant sources of information used throughout this research.

Signature: Vinod Kumar

Date: 01\06\2025

# CERTIFICATE

This is to certify that the thesis titled “**Enhancing Signal Coverage and Performance by Optimization of Router Placement Using Deep Learning Model**" submitted by **Vinod Kumar**, who enrolled for the M.Sc. degree program on **22 August 2023** at the Indian Institute of Information Technology, Lucknow, is the result of his independent research work. The thesis has been carried out under the guidance of **Dr. Deepak Kumar Singh**, Department of IT, Indian Institute of Information Technology, Lucknow - 226002, U.P., India, and **Dr. Madhurima Datta**, Department of Mathematics, Indian Institute of Information Technology, Lucknow - 226002, U.P., India.

To the best of our knowledge, this work has not been submitted previously, in whole or in part, for the award of any degree, diploma, or any other academic recognition at any institution.

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# ABSTRACT

Accurate localization of devices in indoor environments remains a challenging problem due to signal fluctuations caused by obstacles and dynamic movement of nodes (e.g., customer devices). The present study builds on existing work focused on optimizing router placement in Wi-Fi networks using Received Signal Strength Indicator (RSSI) values. In previous studies that utilized an improved RNN with LSTM layers for spatial analysis, these methods have limitations in a single model without exploring broader deep learning alternatives.

In the present study, the reference work is extended by experimenting with a diverse range of advanced deep learning models on the same WiFi RSS fingerprint dataset. We evaluated multiple architectures, including CNN, Bidirectional LSTM, Stacked LSTM, GRU, LSTM with Attention, Conv1D-LSTM, Temporal Convolutional Networks (TCN), and Transformer networks. In the present investigation, an optimum accuracy of 97.44% is achieved by incorporating the LSTM with Attention, Bi-LSTM models, also providing highly accurate results. The present study demonstrates improved results to the original model(improved RNN), demonstrating better adaptability to spatial and temporal variations in indoor signal propagation.

To validate the robustness of the proposed methodology, a new dataset was collected following a standardized data collection process derived from the literature survey. The same set of deep learning models was trained on this dataset and observed consistent performance improvements, with GRU and LSTM-Attention models achieving up to 98.63% accuracy, along with high precision, recall, and F1 scores.

Overall, our research introduces a more comprehensive and comparative deep learning models. This work can assist network engineers and homeowners in designing efficient Wi-Fi layouts while contributing to the field of spatial signal modeling and wireless network optimization.

**Keywords:** Indoor Localization, Wi-Fi, RSSI, Deep Learning, Recurrent Neural Network, LSTM, GRU, Bi-LSTM, Signal Coverage, Router Placement Optimization

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# List of Abbreviations & Notations

## Abbreviations

| | |
|---|---|
| AP | Access Point |
| CNN | Convolutional Neural Network |
| Conv | Convolutional |
| GRU | Gated Recurrent Unit |
| LSTM | Long Short-Term Memory |
| Bi-LSTM | Bi-directional Long Short-Term Memory |
| MSE | Mean Squared Error |
| RNN | Recurrent Neural Network |
| RSSI | Received Signal Strength Indicator |
| TCN | Temporal Convolutional Network |
| Wi-Fi | Wireless Fidelity |
| DL | Deep Learning |
| ML | Machine Learning |
| KNN | k-Nearest Neighbor |
| SVM | Support Vector Machine |

## Notations

| | |
|---|---|
| $x, y, z$ | Coordinates in 3D indoor space |
| $r_i$ | RSSI value from the $i^{th}$ Access Point |
| $\hat{y}$ | Predicted coordinates |
| $y$ | True coordinates |
| $\mathcal{L}$ | Loss function |
| $\mathbf{X}$ | Input feature matrix |
| $n$ | Number of samples |
| $t$ | Time steps in sequence data |

# Chapter 1

# Introduction

## 1.1 Introduction

In today's world of widespread digital interconnectivity, wireless networking has become the foundation of modern communication infrastructure, particularly in indoor settings such as homes, offices, and commercial buildings. The widespread adoption of Wi-Fi networks has driven a growing need for high-performance, low-latency, and seamless internet connectivity. The evolution of wireless standards has culminated in the advent of Wi-Fi 6, or IEEE 802.11ax, which significantly enhances data rates, energy efficiency, and network capacity in dense user environments [4]. Despite these advancements, a core challenge remains unresolved: the optimal placement of routers in indoor spaces to ensure consistent and high-quality wireless coverage.

Indoor environments are inherently complex due to the influence of walls, furniture, human movement, and electronic interference, all of which affect the propagation of wireless signals [20]. These challenges result in fluctuating Received Signal Strength Indicator (RSSI) values, creating signal dead zones and reducing user experience. Traditional approaches to router placement often involve heuristic or manual configuration methods that do not account for dynamic changes in the environment. These methods, although simple, fail to optimize the spatial-temporal characteristics of signal propagation in real-world conditions, leading to suboptimal network performance.

Recent innovations in Artificial Intelligence, particularly within the realm of Deep Learning (DL), offer promising solutions to this problem, have opened new possibilities for intelligent and adaptive network optimization [9] [12]. In this research, we explore a hybrid approach that utilizes RNNs specifically LSTM models, to analyze sequential RSSI data and predict optimal router placements[14]. By learning the spatial and temporal patterns of signal strength variations, deep learning models can significantly outperform conventional techniques in estimating the ideal placement for wireless routers.

Our approach is inspired by and builds upon existing studies Singh et al. (2024), who employed deep learning methods to improve signal coverage and optimize router placement in indoor environments [14] and Alhmiedat (2023), who demonstrated the use of fingerprint-based localization techniques in Wireless Sensor Networks using machine learning models[2]. Following these methodologies, we developed models using both publicly available benchmark datasets and datasets collected in real-world environments. The benchmark dataset used in our study—referenced from [14]—consists of RSSI values gathered from multiple access points within a controlled indoor space. This dataset serves as the foundation for evaluating the baseline performance of various neural network models, including Simple RNN, GRU, Bidirectional LSTM, Conv1D-LSTM, Temporal Convolutional Networks (TCN), and Transformer architectures [16].

Our real-world experimentation extends this study by collecting a dataset with a controlled laboratory environment using a NetSpot RSSI value analyzer mobile application and six fixed access points (Phone devices). Each sample records the RSSI values over a short time sequence while the device is stationary. allowing for temporal pattern recognition. Using the principles outlined in [2], we recorded RSSI fingerprints at 364 reference points while maintaining consistency with the benchmark dataset's attributes. The collected data includes a sequence of signal strengths from six access points over multiple time intervals. This data was then preprocessed and fed into various deep learning models for training and evaluation.

Through comprehensive testing and evaluation, we observed that models incorporating bidirectional and attention-based architectures outperformed others in terms of coordinate prediction accuracy. Specifically, the LSTM with attention and Conv1D-LSTM architectures yielded the lowest MSE and MAE, demonstrating their capacity to learn and represent both temporal dependencies and localized features in the RSSI sequences [6]. The models trained on our dataset also performed robustly, with minimal overfitting, indicating the generalizability of our approach to different environments.

## 1.2 Motivation

The primary motivation behind this research lies in addressing the limitations of traditional router placement techniques by harnessing the capabilities of deep learning [10]. By accurately modeling the behavior of Wi-Fi signals within complex indoor environments, Our aim to enhance user experience by minimizing connectivity gaps and improving overall network performance. Our research is guided by the following core objectives:

The current landscape of wireless networking often struggles with signal degradation, interference, and inefficient coverage in indoor settings, especially as device density increases with the proliferation of smart technologies. Traditional methods for placing routers, such as heuristic rules or static floor plan evaluations, frequently fail to adapt to dynamic and obstruction-filled indoor spaces. These shortcomings create a compelling need for intelligent, data-driven methods that can understand and adapt to complex spatial patterns of signal distribution. The emergence of deep learning, especially RNNs and their variants like LSTM, offers powerful tools capable of learning temporal and spatial signal behaviors from RSSI data. This research is driven by the desire to exploit these capabilities to predict optimal router positions that can dynamically adjust to real-time changes in the environment[14], thus ensuring robust and consistent wireless coverage.

## 1.3 Research Objectives

Based on this motivation, the research outlines three primary objectives. Primarily, to develop a deep learning model capable of learning patterns from RSSI fingerprints and intelligently propose optimal indoor router placements[14]. Second, to compare and evaluate the effectiveness of different neural network architectures—Simple RNN, CNN, and LSTM—in predicting accurate locations using both a benchmark dataset and a self-collected dataset designed with real-world applicability in mind. Third, to visually interpret the localization and placement results using performance metrics such as RMSE, MAE, and classification accuracy, thus offering a comprehensive understanding of which model architecture is most suitable for practical deployment in Wi-Fi 6 environments. Through these objectives, the research seeks to bridge the gap between theoretical advancements in deep learning and their practical application in next-generation wireless networking systems.

## 1.4 Dataset Collection Strategy

To ensure that deep learning model was grounded in realistic and reproducible data, we collected dataset with controlled laboratory environment using a NetSpot RSSI value analyzer Mobile Application and six fixed access points (Phone devices).Each sample records the RSSI values over a short time sequence while the device is stationary, allowing for temporal pattern recognition. Inspired by the technique proposed by Alhmiedat (2023) [2], we deployed six access points uniformly across the lab and recorded RSSI values at predefined grid points covering the 10.058x12.192 $m^2$ area. A mobile device was used to scan RSSI signals over some time, capturing fluctuations due to interference, user movement, and environmental changes. Each scan produced a sequence of signal strength readings from all access points. These sequences were timestamped and labeled with the ground-truth coordinates (X, Y, Z) of the device, enabling supervised learning. The resulting dataset contained 364 training samples with three-timestep sequences and an additional seven samples reserved for real-world testing. The collected dataset adhered to the same schema as the reference benchmark, facilitating comparative analysis.[2]

## 1.5 Contribution of Research

This study offers the following significant contributions:

- **Innovative Methodology:** Introduction of a hybrid model that combines deep learning (RNN, LSTM) for adaptive router placement in Wi-Fi networks.
- **Real-World Dataset Integration:** Development and deployment of a collected RSSI dataset aligned with benchmark attributes for real-world evaluation.
- **Comprehensive Model Comparison:** In-depth analysis of various sequential neural networks and hybrid models to identify the optimal architecture for localization.
- **Dynamic Adaptation:** Implementation of adaptive feedback mechanisms to adjust router placement based on real-time signal changes and user mobility.
- **Enhanced User Experience:** Optimization strategies aimed at reducing packet loss, increasing throughput, and maintaining stable connectivity in high-density environments.

## 1.6 Organization of the Paper

The structure of the remaining sections is as follows: Section 2 reviews the existing literature and foundational studies related to Wi-Fi-based indoor localization. Section 3 outlines the methodology adopted, covering dataset preparation, model design, and training settings. Section 4 discusses the experimental results and compares the performance of various deep learning models. Section 5 illustrates a real-world application and practical implementation of the proposed method. Finally, Section 6 summarizes the key outcomes, discusses current limitations, and suggests directions for future work.

# Chapter 2

# Literature Review

Singh et al. (2024) present a deep learning-based approach aimed at improving Wi-Fi signal coverage and optimizing router placement in indoor environments [14]. The study addresses challenges in signal attenuation and interference by employing neural network models to identify optimal router positions within complex indoor spaces. By utilizing real-world RSSI data and evaluating CNN, Simple RNN and Improved RNN architectures, the authors demonstrate a notable improvement in signal distribution and network performance in the indoor environment. While the results highlight the efficacy of deep learning in enhancing wireless connectivity, the work primarily concentrates on signal coverage rather than precise user localization. Future research could extend this framework by integrating spatiotemporal learning models, such as LSTM or Transformer networks, to capture the dynamic behavior of Wi-Fi signals and support both coverage and user tracking simultaneously.

Alhmiedat et al. (2023) introduce a fingerprint-based indoor localization system tailored for Wireless Sensor Networks (WSNs) that leverages machine learning techniques to achieve cost-effective and reliable positioning in complex indoor environments [2]. By constructing a bespoke dataset and experimenting with various machine learning models, the authors achieve an average localization error of 1.4 meters, demonstrating strong performance despite the presence of walls and obstructions. While the study yields promising results, it focuses primarily on traditional machine learning models and overlooks the potential benefits of deep learning. Future extensions could involve incorporating temporal sequence modeling through architectures Using RNNs or LSTM networks allows for better modeling of the changing behavior of indoor RSSI signals over time.

In their 2024 study, Alhmiedat and Istepanian propose a deep learning-based solution for optimizing router placement in indoor Wi-Fi networks [3]. Their work evaluates spatial configurations and signal propagation to identify optimal router positions that minimize dead zones and enhance overall signal strength and network performance. This approach is particularly beneficial for complex environments with multiple physical barriers. Despite its effectiveness in improving coverage, the model does not account for variations in user movement or real-time environmental changes. Enhancing this work with adaptive or reinforcement learning algorithms could allow routers to dynamically adjust their locations or signal parameters based on changing user behavior and real-time feedback.

Kim et al. (2021) present a CNN-based system that leverages Channel State Information (CSI) collected along motion trajectories for indoor localization, diverging from traditional point-based fingerprinting [8]. The model incorporates Generative Adversarial Networks (GANs) to augment training data, reducing manual data collection and enhancing robustness. Although the approach demonstrates strong localization performance, its reliance on CSI may limit applicability in systems that predominantly utilize RSSI data. Future directions may include developing hybrid models that combine CNNs with RNNs to learn both spatial and temporal signal characteristics or implementing domain adaptation strategies to bridge the gap between CSI and RSSI-based datasets.

Meng et al. (2020) offer a comprehensive survey of deep learning applications in localization, encompassing methods like Simultaneous Localization and Mapping (SLAM), visual odometry, and fingerprinting [11]. The paper categorizes various architectures based on their strengths in accuracy, adaptability, and environmental robustness. However, the survey lacks comparative experimental benchmarks across standardized datasets, making it difficult to assess the practical utility of different models. Future efforts could involve building a unified framework for empirical evaluation, allowing researchers to compare deep learning models under consistent conditions across diverse environments.

Alhmiedat et al. (2023) explore the strategic deployment of Wi-Fi 6 (IEEE 802.11ax) within smart environments to enhance support for simultaneous digital services like video conferencing, voice communication, and large file transfers [1]. They develop a decision-making algorithm that evaluates network parameters such as throughput, latency, and service type to determine optimal WLAN configurations. The study significantly contributes to the creation of efficient, multi-service indoor networks. However, the model does not address the impact of user density fluctuations or dynamic environmental changes. Advancing this research could involve integrating reinforcement learning techniques capable of real-time optimization under varying network loads and conditions.

LeCun, Bengio, and Hinton (2015) offer a comprehensive foundational overview of deep learning, highlighting the capabilities of core architectures like CNN and RNNs, and autoencoders [9]. The paper emphasizes the hierarchical representation learning power of deep models, Their work has been a key driver of advancements in fields such as computer vision and natural language processing. While the work is foundational, it precedes the emergence of newer architectures like transformers and attention mechanisms, which have since revolutionized deep learning. Future explorations could examine the application of these advanced models to indoor localization and wireless networking challenges.

Yassin et al. (2017) present a broad survey of indoor localization technologies, ranging from Wi-Fi and RFID to Ultra-Wideband (UWB), and evaluate each based on factors such as cost, accuracy, and environmental adaptability [19]. The review provides valuable insights into the trade-offs of different technologies. However, it places greater emphasis on hardware-based solutions while offering limited discussion on machine learning-driven methods. Subsequent research could explore hybrid systems that combine sensor hardware with data-driven models to improve adaptability and reduce infrastructure costs in real-world settings.

He et al. (2021) propose a device-free localization system that utilizes Wi-Fi Channel State Information (CSI) in conjunction with deep learning models to track individuals passively, eliminating the need for users to carry dedicated devices [5]. This approach holds promise for privacy-preserving applications and non-intrusive monitoring. However, the system's performance is highly affected by environmental variations, such as furniture rearrangements or the presence of multiple people. Future work could focus on developing adaptive learning models capable of continuous self-updating with minimal human intervention, enhancing the system's robustness in dynamic indoor spaces.

Al-Jarrah et al. (2023) examine the role of artificial intelligence in optimizing wireless networks, highlighting use cases like dynamic channel allocation and behavior-aware resource management [7]. Their analysis presents AI as a key enabler of autonomous and context-aware network optimization. Despite offering conceptual frameworks and simulation results, the study lacks real-time deployment or validation in live environments. Future studies could test these AI models in operational networks to evaluate scalability, latency, and adaptability under realistic usage scenarios.

Wu et al. (2023) present a deep learning framework for indoor localization that uses autoencoders and feedforward neural networks to process Wi-Fi-based signal features [17]. The model demonstrates high accuracy in mapping RSSI data to physical locations in static environments. Nonetheless, it assumes consistent signal patterns and does not address dynamic conditions such as user movement or environmental changes. Future research may incorporate temporal sequence models like RNNs or LSTMs to enhance performance in scenarios involving mobility or frequent layout alterations.

Zhang et al. (2020) analyse the use of Recurrent Neural Networks to model temporal variations in RSSI values for indoor localization [21]. Their findings indicate substantial improvements in localization accuracy over traditional non-sequential approaches. However, the study does not explore more advanced variants of RNNs such as Gated Recurrent Units (GRUs) or attention-based mechanisms. Expanding this line of research to include these enhancements could yield further accuracy improvements, especially in environments with complex temporal signal patterns.

Torres-Sospedra et al. (2015) introduce the UJIIndoorLoc dataset, a benchmark for evaluating large-scale indoor localization systems spanning multiple buildings and floors [15]. The study outlines data collection strategies and highlights challenges in developing scalable fingerprint databases. While the dataset has become a standard in the field, it represents static snapshots and does not support real-time adaptability. Future enhancements could involve automated data collection via mobile devices and self-labeling techniques to maintain up-to-date and context-aware fingerprint maps.

Mohammed et al. (2022) design a deep learning-based indoor positioning model that prioritizes low latency and high accuracy for real-time applications [13]. The model effectively processes Wi-Fi RSSI fingerprints, achieving precise localization in near real-time. However, the system's generalizability across different indoor environments is limited due to the specificity of training data. Future directions could focus on incorporating transfer learning to reduce the need for environment-specific retraining and broaden applicability across diverse deployment scenarios.

Xu et al. (2021) propose a LSTM model integrate with transfer learning to accelerate adaptation to new indoor environments without extensive data collection [18]. This approach enables the model to learn temporal dependencies while reusing knowledge from related tasks or settings. Despite its benefits, the success of transfer learning heavily depends on the compatibility between source and target domains. Future research could explore meta-learning strategies that improve generalization across a wider range of localization contexts.

# Chapter 3

# Methodology

## 3.1 Overview

This study implements and compares deep learning architectures for indoor localization and optimal router placement using Wi-Fi RSSI data. The aim is to predict precise $X$, $Y$ and $Z$ coordinates based on sequences of RSSI readings from multiple access points. Two datasets were utilized: a published benchmark dataset [2] and a real-world lab dataset collected under similar conditions.

## 3.2 Dataset Description

### 3.2.1 Reference Dataset

The reference dataset used in this research was obtained from Alhmiedat [2], designed for Wi-Fi RSSI-based indoor localization. It contains 194 reference points, each consisting of a short sequence of RSSI values from four access points. Each sample represents the RSSI readings at a specific indoor position, paired with the corresponding ground truth $(X,Y)$ coordinates. Each sample contains 4 timesteps with 1 features per timestep, structured as:

r1, r2, r3, r4 RSSI readings $\rightarrow$ reshaped into (4,1): $(r1),(r2),(r3),(r4)$

### 3.2.2 Real-World Collected Dataset

A real-world dataset was collected in a controlled laboratory environment using a NetSpot RSSI value analyzer mobile application and six fixed access points (Phone devices). It contains 364 reference points with the corresponding ground truth $(X,Y,Z)$ coordinates, each consisting of a short sequence of RSSI values from four access points while the device is stationary. This dataset mirrors the format of the reference dataset but uses actual RSSI readings gathered via real-time scanning.[2]

- Total reference points: 364 (for testing and validation)
- Each sample point : a sequence of RSSI readings from 6 access points

Processed to resemble the shape of the Real-World Collected Dataset, ensuring a consistent input format across both datasets.

RSSI readings from access points were grouped as:

$$(AP1, AP2), (AP3, AP4), (AP5, AP6) \quad \rightarrow \quad \text{resulting in 3 timesteps } \times 2 \text{ features (shape: } (3, 2))$$

## 3.3 Data Preprocessing

Both datasets underwent the same preprocessing pipeline to ensure compatibility across all deep learning models. The following steps were executed:

### 3.3.1 Missing Value Handling:

RSSI values of 0 or any null entries were treated as invalid readings and replaced with a minimum detectable signal (e.g., $-100\,\text{dBm}$) or mean imputation based on nearby samples.

### 3.3.2 Normalization:

All RSSI values were normalized to a $[0, 1]$ range using Min-Max scaling:

$$\text{RSSI}_{\text{norm}} = \frac{\text{RSSI} - \text{min}}{\text{max} - \text{min}}$$

where min $= -100$, max $= -30$.

### 3.3.3 Reshaping for Model Input:

Different models required specific input shapes:

#### 3.3.3.1 Reshaping of Reference Dataset

- RNN, LSTM, GRU models: Input shape $(4, 1)$ – flattened and reshaped from RSSI sequence.
- Attention and Transformer models: Input shape $(4, 1)$ – full temporal sequence preserved.
- Conv1D-based models: Required consistent timestep dimension $\rightarrow$ reshaped to $(2, 2)$ or $(4, 1)$ depending on convolution strategy.

#### 3.3.3.2 Reshaping of Real-World Collected Dataset

- RNN, LSTM, GRU models: Input shape $(3, 2)$ – flattened and reshaped from RSSI sequence.
- Attention and Transformer models: Input shape $(3, 2)$ – full temporal sequence preserved.

- Conv1D-based models: Required consistent timestep dimension $\rightarrow$ reshaped to $(3, 2)$ depending on convolution strategy.

## 3.4 Proposed Model Justification and Comparative Analysis

### 3.4.1 Suitability of Proposed Models for RSSI-Based Sequential Data

The suggest deep learning models Bi-LSTM, GRU, and LSTM with Attention were selected because of their high capability in modeling time-series and sequential data, which aligns with the structure of both Datasets utilized in this research. The first dataset, based on the reference model of Alhmiedat (2023) [2], consists of simulated RSSI values generated in a controlled indoor environment. The second dataset, collected in a real lab setup, includes actual RSSI values captured over time from six access points. In both cases, the data comprises short sequences of received signal strength, which are inherently sequential and influenced by environmental noise, signal interference, and temporal changes.

Standard feedforward models are limited in learning time dependencies, especially in sequences that involve subtle variations due to user movement, signal fading, and occlusion. Therefore, it is essential to employ models that can remember past information and context. Bidirectional LSTM is effective in learning relationships in both forward and backward directions across a sequence. GRU simplifies the LSTM architecture while maintaining performance, making it suitable for smaller datasets with limited temporal depth. LSTM with Attention further enhances performance by dynamically attending to the most relevant time steps during prediction, which is beneficial when specific RSSI readings carry more weight in determining the location.

### 3.4.2 Superiority of Proposed Models over CNN, RNN, and Standard LSTM

Previous studies have used CNNs, RNNs, and basic LSTM networks for RSSI-based localization tasks. CNNs perform well for spatial features and are commonly used in image-based localization or when spatial patterns dominate. However, CNNs lack the memory mechanism needed for capturing time-series dependencies in RSSI values, especially over short sequences. RNNs, while designed for sequences, suffer from vanishing gradients and are limited in their ability to retain long-term context. LSTM partially addresses this issue by introducing memory gates, but it processes sequences in only one direction, which may overlook contextual information coming from the end of a sequence.

In contrast, Bidirectional LSTM captures signal dependencies from both the beginning and end of a sequence, which is useful when RSSI values fluctuate due to changing user positions within a short interval. GRU simplifies this further with fewer parameters, which helps reduce overfitting when training on smaller datasets like the real-world collected data. Attention-based LSTM goes a step further by identifying which time steps are most important for the final output, which is especially useful in noisy datasets where some RSSI readings may be misleading or less informative.

### 3.4.3 Implementation and Configuration of Proposed Architectures

The Bidirectional LSTM model used in this study consists of two LSTM layers operating in opposite directions. The forward layer processes the sequence as usual, while the backward layer reads it in reverse. Their outputs are concatenated and passed to a fully connected dense layer. This structure ensures that both past and future context are considered, which improves accuracy for localization tasks involving time-varying signal strengths. The configuration was optimized using dropout layers to prevent overfitting and ReLU activation for non-linearity.

The GRU model was implemented using a single-layer GRU unit followed by a dropout layer and dense layer for regression output. GRUs require fewer training iterations and offer good generalization when training data is limited, as was the case in the lab dataset (364 samples). Despite their simpler architecture, GRUs maintain strong temporal learning capabilities through their reset and update gates.

The LSTM with Attention architecture used a standard LSTM layer followed by a custom attention layer. The attention mechanism computes weighted scores for each time step, enabling the model to emphasize the most informative RSSI readings. This is particularly valuable in real-world environments where signal noise and variability can impact the usefulness of certain measurements. The output of the attention layer is fed into dense layers to produce the final predictions.

The Conv1D + Bi-LSTM model was designed to leverage both convolutional and recurrent layers for enhanced feature extraction and sequence processing. It begins with a Conv1D layer featuring 64 filters and a kernel size of 2, using ReLU activation to capture local patterns in the input data (shape: 3 timesteps, 2 features). This is followed by a Bidirectional LSTM layer with 64 units, processing the sequence in both directions to incorporate contextual information from past and future timesteps, with return sequences enabled. A dropout layer (0.3 rate) and batch normalization are applied to mitigate overfitting and stabilize training. The sequence is then passed to a second LSTM layer with 32 units for deeper temporal learning, followed by a dense layer with 64 units (ReLU activation) and a final dense layer with 3 units (linear activation) to predict the x, y, z coordinates. This architecture excels in handling spatial-temporal data for localization tasks.

### 3.4.4 Benefits and Performance of Proposed Models

Each of the proposed models offers unique advantages tailored to the nature of the datasets. Bidirectional LSTM improved the model's understanding of bidirectional dependencies, which is useful for sequences of RSSI values where the signal at time t may depend on both earlier and later signal behavior. GRU showed efficient training performance with comparable accuracy, especially beneficial in cases with less training data and lower sequence depth. LSTM with Attention provided a fine-grained understanding of sequence relevance, making it highly effective for predicting accurate locations in the presence of irregular signal strength changes.

Experimental results confirmed that the proposed models outperformed baseline models in both regression (MAE, RMSE) and classification (accuracy, precision) metrics across both datasets. Their robustness to noise, ability to generalize, and compatibility with short time-series data make them well-suited for real-world indoor localization applications using Wi-Fi RSSI data.

## 3.5 Deep Learning Models and Architectures

The following architectures achieved performance equal to or greater than the improved RNN and are therefore included in this study:

### 3.5.1 Bidirectional LSTM

This model employs a Bidirectional LSTM to learn temporal patterns from both past and future contexts, enhancing its capacity to capture detailed sequential dependencies. The configuration includes:

- Bidirectional LSTM with 64 units.
- Dense layers (32, 2 units).
- Dropout, ReLU activation, and L2 regularization.

### 3.5.2 GRU

The GRU model offers a simplified alternative to LSTM by using fewer gates, making it faster and effective for small datasets. The configuration includes:

- GRU layer with 64 units.
- Dense layers (32, 2 units).
- Dropout and ReLU activation.

### 3.5.3 LSTM with Attention

This model integrates the memory strength of LSTM networks with attention mechanism that dynamically focuses on the most relevant time steps during prediction. The architecture includes:

- One LSTM layer with 64 units.
- An Attention layer to weigh outputs from the LSTM.
- Dense layers with 64 and 2 units respectively.
- ReLU activation and Mean Squared Error loss.

### 3.5.4 Conv1D + Bidirectional LSTM

This architecture integrates a Conv1D layer with a Bidirectional LSTM to identify local signal patterns and model long-range dependencies in both time directions, thereby improving the extraction of spatial-temporal features. The configuration includes:

- Conv1D layer with 64 filters and kernel size of 2, using ReLU activation.
- Bidirectional LSTM with 64 units, return sequences enabled.
- Dropout (0.3 rate) and Batch Normalization.
- LSTM layer with 32 units.
- Dense layers (64 units with ReLU, 3 units with linear activation).

## 3.6 Flowchart of the Proposed Methodology

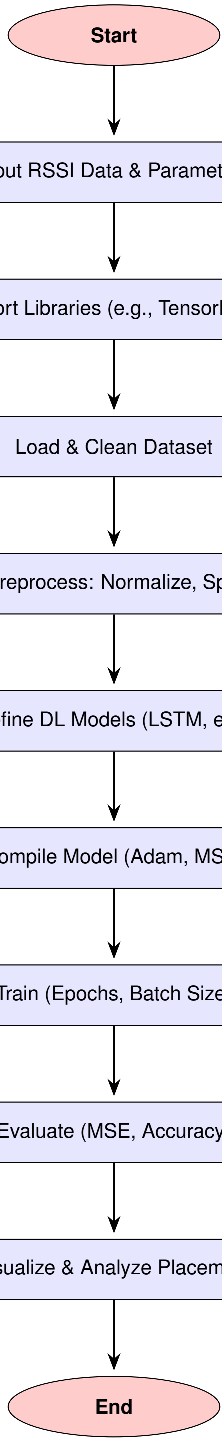


Figure 3.1: Flowchart of the proposed methodology for RSSI-based indoor localization using deep learning.

## 3.7 Algorithm for the Proposed Approach

The proposed methodology is designed to optimize router placement and improve localization accuracy in indoor Wi-Fi environments using deep learning architectures. Due to the complexity of signal propagation in indoor spaces, traditional methods often fail to deliver precise localization. This approach leverages robust temporal sequence models such as Bidirectional LSTM, GRU, and LSTM with Attention to learn spatial patterns from RSSI values and predict target coordinates effectively.

### 1) Proposed Workflow

**a) Input:**

- **RSSI Datasets:**
  - **Reference Dataset (Alhmiedat, 2023)[2]:** Includes 194 samples, each with a sequence of RSSI values from four fixed access points ($r_1$, $r_2$, $r_3$, $r_4$), measured over 4 time steps, with 1 features per timestep.
  - **Real-world Lab Dataset (Collected):** Includes 364 samples. Each sample also contains a sequence of RSSI values from the same four access points over 3 time steps with 2 feature per timestep.
- **Model Parameters:** Includes configuration for each model such as the number of units in recurrent layers (e.g., 64), dropout rate (e.g., 0.3), learning rate (e.g., 0.001), number of epochs (e.g., 100), batch size (e.g., 32), and threshold distance (e.g., 6.5) for accuracy evaluation.

**b) Output:**

- **Loss Values:** Includes training and validation loss metrics over epochs.
- **Evaluation Metrics:** MSE, RMSE, and localization accuracy based on a threshold distance.
- **Predicted Coordinates and Visualization:** Predicted coordinates ($\hat{x}$, $\hat{y}$, $\hat{z}$), plotted against ground-truth locations. Also highlights coordinates with optimal signal strength.

### 2) Step-by-Step Implementation

1. **Import Libraries and Frameworks:** Import essential libraries like `NumPy`, `Pandas`, `Seaborn`, and modules from `scikit-learn` (e.g., `train_test_split`, `mean_squared_error`), and `TensorFlow/Keras` (e.g., `Sequential`, `LSTM`, `GRU`, `Conv1D`, `Dense`, `Dropout`, `Bidirectional`).
2. **Load and Clean Dataset:**
   - Read the CSV file containing RSSI sequences and their associated coordinates.

- Clean the dataset by removing missing values and trimming whitespace from column headers.

3. **Preprocess the Data:**
   - Separate features (RSSI sequences) and labels (coordinates).
   - Normalize the RSSI values for better training convergence.
   - Divide the dataset into separate subsets for training and testing purposes.
   - **Reshape the feature matrices for RNN-based models:**
     - **Reference Dataset:** Reshaped to 3D input of shape `(samples, 4 timesteps, 1 features)` → shape: `(194, 4, 1)`.
     - **Real-world Dataset:** Reshaped to shape `(364, 3 timesteps, 2 feature)` → shape: `(364, 3, 2)`.

4. **Define Deep Learning Architectures:**
   - **Bidirectional LSTM:** One Bidirectional LSTM layer with 64 units followed by dropout and dense layers (32 and 2 units) with ReLU and linear activations respectively.
   - **GRU:** One GRU layer with 64 units followed by dropout and dense layers.
   - **Conv1D + Bidirectional LSTM:** One Conv1D layer (64 filters, kernel size = 2) followed by a Bidirectional LSTM, and dense layers for regression.

5. **Compile the Models:**
   - Use `Adam` optimizer with a learning rate of 0.001.
   - Use `MSE` as the loss function.

6. **Train the Models:**
   - Train each model using the training set for 100 epochs with a batch processing.
   - Use the validation set to monitor training performance and prevent overfitting.

7. **Evaluate Model Performance:**
   - Predict coordinates on the test set.
   - Calculate MSE, RMSE, and threshold-based accuracy by measuring Euclidean distance between predicted and true positions.

8. **Visualize Results:**
   - Plot training vs. validation loss curves over epochs.
   - Scatter plot comparing predicted and actual coordinates.
   - Highlight the predicted point with the strongest RSSI values as an optimal placement location.

# Chapter 4

# Simulation and Results

## 4.1 Dataset

This research utilized two separate datasets to train, validate, and assess the effectiveness of the proposed deep learning models for indoor localization based on Wi-Fi RSSI signals. The first dataset is from a literature survey,[2], while the second was gathered in an actual indoor laboratory setting. Each dataset includes RSSI measurements from multiple access points along with the associated spatial coordinates, providing an appropriate foundation for location estimation tasks.

### 4.1.1 Reference Dataset

The first dataset, referred to as the RSSISensors dataset[2], was collected in a structured indoor laboratory setting. It consists of 194 samples, where each sample records RSSI values from four access points—denoted as $r1$, $r2$, $r3$, and $r4$—alongside the corresponding $X$ and $Y$ coordinates of the receiver device. The coordinate values span a range of $X = 0$ to 20 meters and $Y = 1$ to 6 meters, outlining a rectangular measurement area approximately 20 meters long and 6 meters wide. This controlled spatial distribution indicates that data collection followed a grid-like layout, which helps ensure uniform spatial sampling.

The RSSI values within this dataset range from 0 to 110. Higher values, approaching 110, typically signify proximity to an access point, whereas values near 0 may indicate signal obstruction or absence due to interference or multipath effects. The RSSI distribution across access points—such as $r1$ ranging from 0 to 107 and $r2$ from 0 to 97—reflects typical indoor wireless propagation characteristics, including reflections, path loss, and signal fading.

Preprocessing steps were applied to improve data quality and compatibility with sequential deep learning models. All rows containing missing or null values were removed using the `df.dropna()` function. To fit the input requirements of different model architectures, the data was reshaped into formats such as $(194, 2, 2)$ or $(194, 4, 1)$ depending on the specific model's input layer configuration. For model evaluation, the dataset was divided into 155 training samples and 39 testing samples, ensuring a consistent and balanced partitioning for learning and performance analysis.

### 4.1.2 Real-World Collected Dataset

The second dataset, referred to as the real-world dataset collected using the litrature suvey approach[2], in an actual indoor controlled laboratory environment using a NetSpot RSSI value analyzer mobile application and six fixed access points (Phone devices). This dataset comprises 364 samples, each containing RSSI values from six access points, labeled $AP1$ through $AP6$, along with corresponding spatial coordinates in three dimensions: $X$, $Y$, and $Z$. The coordinates range from $X = 0$ to 10.0584 meters, while $Y = 0$ to 12.192 meters and $Z = 4.572$ meters. This distribution suggests that the movement of the device was restricted along a linear or narrow space—potentially a hallway or aisle—while maintaining a constant height and depth.

RSSI values in this dataset range from approximately −45 to −78 dBm, a scale typical for RSSI measurements in dBm format. Values closer to −45 dBm indicate strong signal reception near an access point, while weaker signals around −78 dBm are likely due to distance, obstruction, or interference. The variation in signal strengths reflects real-world conditions such as multipath propagation, signal attenuation through walls or objects, and environmental noise.

To prepare the data for model input, similar preprocessing procedures were followed. Samples with missing values were removed, and the data was reshaped into a three-dimensional format of $(364, 3, 2)$. This configuration allows each model to process sequences of three time steps with two features, matching the temporal structure expected by recurrent and attention-based models.The dataset was split into 291 samples for training and 73 for testing, maintaining an approximate 80-20 ratio that supports robust generalization.

### 4.1.3 Independent Real-World Collected Test Dataset

In addition to the primary real-world dataset, a separate set of 7 reference points was collected independently to serve as an external test set. This small dataset also contains RSSI values from $AP1$ to $AP6$ and the corresponding true $X$, $Y$, and $Z$ coordinates. The coordinate values in this set are consistent with the range observed in the primary real-world dataset, confirming that it represents the same physical environment. The RSSI values fall within the same range of −45 to −78 dBm, indicating similar signal propagation characteristics and ensuring comparability.

Although the small sample size of this external test set limits statistical generalization, it serves a critical role in evaluating the models' ability to generalize beyond the training data. The inclusion of this dataset offers insights into how the models would perform in a practical deployment scenario, where previously unseen signal patterns and environmental dynamics may arise. For consistency, the samples were reshaped to $(7, 3, 2)$ format, aligning with the input expectations of all proposed models.

## 4.2 Models Loss Analysis

### 4.2.1 Reference Dataset

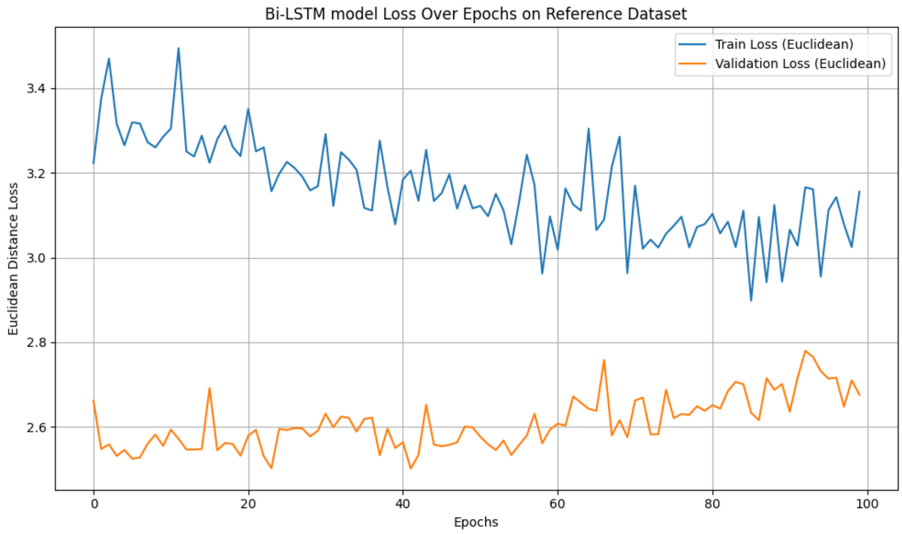


Figure 4.1: Bi-LSTM model Loss Over Epochs on Reference Dataset

Figure 4.1 illustrates the training and validation Euclidean loss of a Bi-LSTM model over 100 epochs using the reference dataset. The training loss shows a downward trend but remains volatile, fluctuating between 2.9 and 3.2 by the end. In contrast, the validation loss remains consistently lower and more stable, ranging from 2.6 to 2.8. The unexpected lower validation loss may also indicate that the validation set is easier or more consistent than the training set.

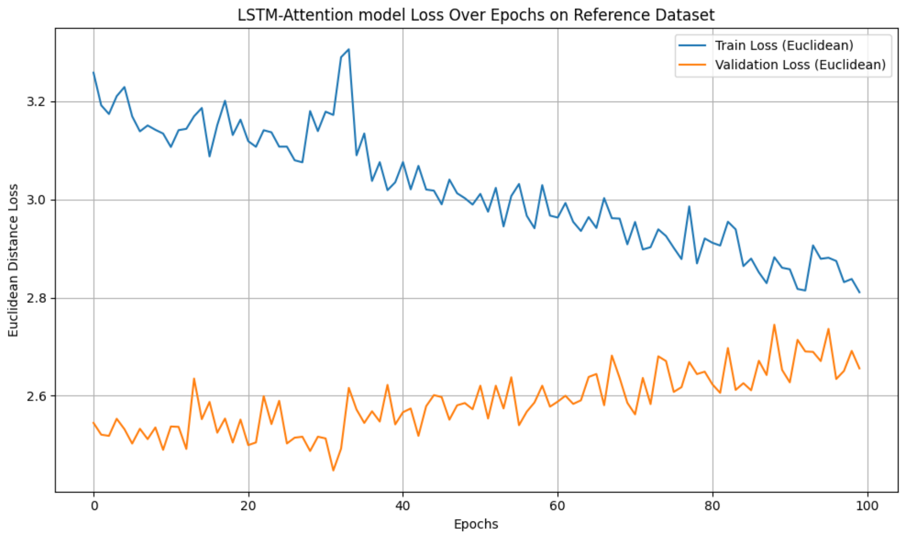


Figure 4.2: Bi-LSTM with Attention model Loss Over Epochs on Reference Dataset

Figure 4.2 shows the Euclidean loss of an LSTM-Attention model during training and validation over 100 epochs using a reference dataset. The training loss fluctuates significantly, peaking around epoch 35 before gradually decreasing to about 2.8 by the end. In contrast, the validation loss remains consistently lower and more stable, ending near 2.7. This consistent gap suggests that the validation data may be simpler or that regularization applied during training is inflating the loss. The stable validation curve implies that the model generalizes well despite fluctuations in training performance.

### 4.2.2 Real-World Collected Dataset

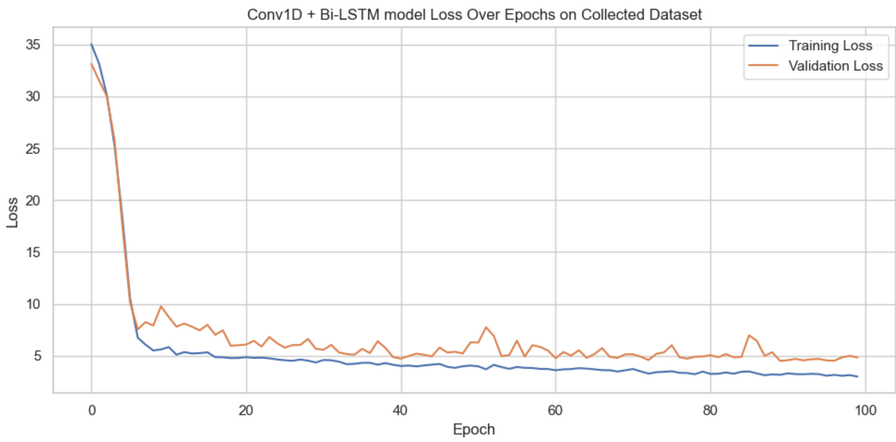


Figure 4.3: Conv1D + Bi-LSTM model Loss Over Epochs on Collected Dataset

Figure 4.3 depicts the training and validation loss of the Conv1D + Bi-LSTM model over 100 epochs using a collected dataset. Both losses start high and decrease rapidly in the early stages, indicating fast initial learning. The training loss steadily declines and stabilizes around 3–4, while the validation loss settles slightly higher, around 5–7, with minor fluctuations. The consistent gap between the two suggests good learning with mild overfitting. Overall, the model shows effective training and reasonable generalization.

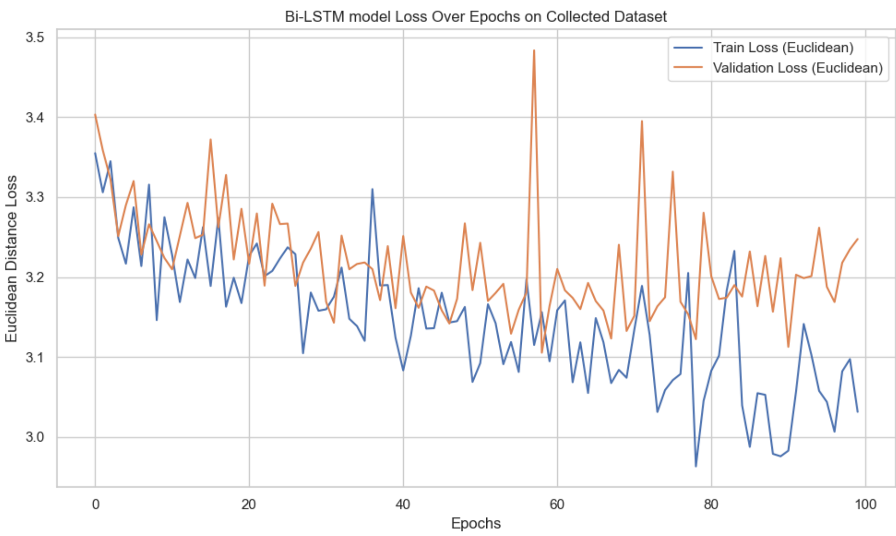


Figure 4.4: Bi-LSTM model Loss Over Epochs on Collected Dataset

Figure 4.4 shows the Bi-LSTM model's training and validation loss over 100 epochs on a collected dataset, measured using Euclidean distance. Both losses begin around 3.4 and fluctuate between 3.0 and 3.5 throughout training. While the training loss remains close to the validation loss, the latter experiences noticeable spikes around epochs 60 and 80. By the end, both losses stabilize near 3.1–3.2, suggesting that model performance has plateaued.

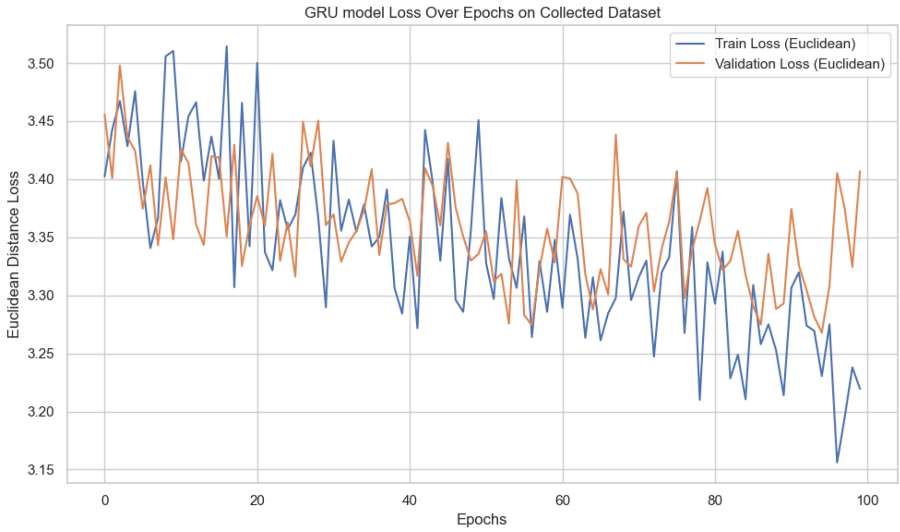


Figure 4.5: GRU model Loss Over Epochs on Collected Dataset

Figure 4.5 presents the GRU model's training and validation loss over 100 epochs on a collected dataset using Euclidean distance as the metric. Both losses begin near 3.5 and fluctuate within the 3.15 to 3.50 range throughout training. The training loss exhibits more noticeable variations, while the validation loss remains comparatively stable with slight peaks. By the final epoch, the training loss decreases to about 3.15, with the validation loss slightly higher, suggesting stable learning without clear signs of overfitting.

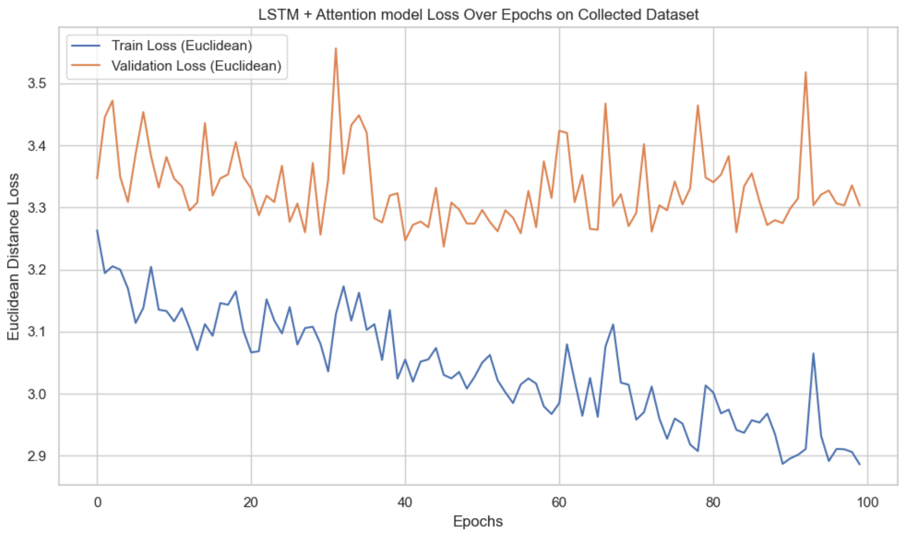


Figure 4.6: LSTM with Attention model Loss Over Epochs on Collected Dataset

Figure 4.6 shows the LSTM with Attention model's training and validation loss across 100 epochs using Euclidean distance. The training loss steadily declines from around 3.3 to approximately 2.9, indicating effective learning. In contrast, the validation loss remains higher, fluctuating between 3.2 and 3.5, with several peaks throughout. By the end of training, the gap between the two losses suggests possible overfitting, as the model performs better on training data than on unseen data.

## 4.3 Results

### 4.3.1 Results on Reference Dataset

The models were evaluated using regression metrics (RMSE, MAE, MSE, $R^2$, Euclidean Distance) and classification metrics (accuracy, precision, recall, F1-score) with a 6.5 meter threshold. The results are presented in the tables below.

Table 4.1: Previous study Results on Reference dataset

| Model | Accuracy (%) | Precision | Recall | F1 Score |
|---|---|---|---|---|
| RNN | 88.61 ± 5.47 | 1.00 ± 0.00 | 0.89 ± 0.05 | 0.94 ± 0.03 |
| CNN | 69.54 ± 7.38 | 1.00 ± 0.00 | 0.70 ± 0.07 | 0.82 ± 0.05 |
| Improved RNN | **93.25 ± 6.10** | 1.00 ± 0.00 | 0.93 ± 0.06 | 0.96 ± 0.03 |

Table 4.2: Our study Results on Reference Dataset

| Model | Accuracy (%) | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Bidirectional LSTM | **97.44** | 1.00 | 0.97 | 0.99 |
| LSTM with Attention | **97.44** | 1.00 | 0.97 | 0.99 |

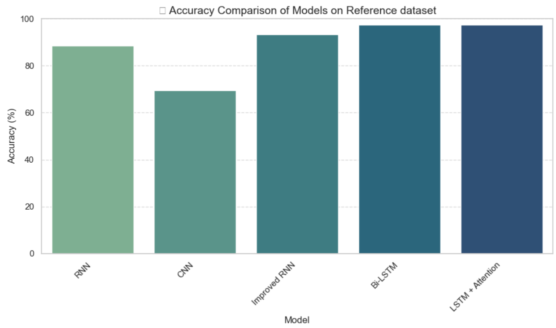


Figure 4.7: Accuracy Comparison of Models on Reference Dataset

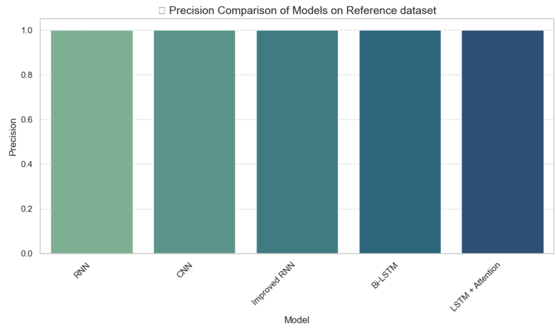


Figure 4.8: Precision Comparison of Models on Reference Dataset

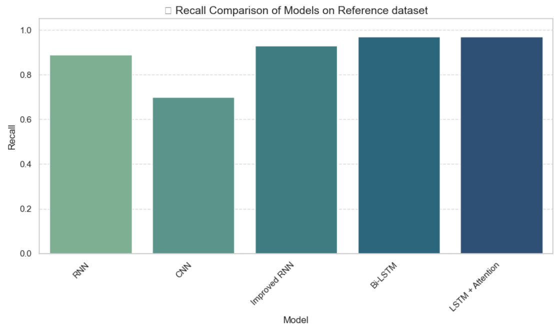


Figure 4.9: Recall Comparison of Models on Reference Dataset

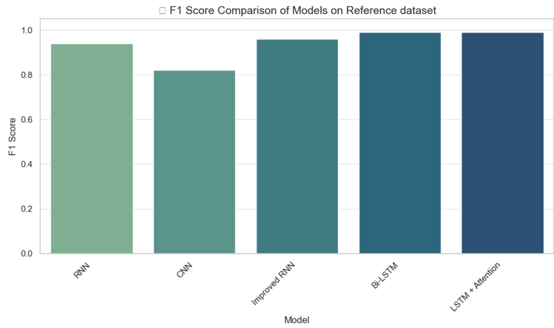


Figure 4.10: F1 Score Comparison of Models on Reference Dataset

### 4.3.2 Interpretation of Previous Study and Our Study Results on Reference Dataset

**Accuracy:** In terms of overall classification accuracy RNN with 88.61%, CNN with 69.54%, and Improved RNN achieved 93.25%. Bidirectional LSTM and LSTM with Attention attain the highest accuracy of **97.44%**, confirming their superior ability to correctly classify instances across the dataset.

**Precision:** CNN, RNN, Improved RNN, Bidirectional LSTM, and LSTM with Attention—achieve a perfect precision score of 1.00. This indicates that whenever any of these models predicts a positive class (i.e., optimal router placement), the prediction is always correct, with no false positives. High precision is especially important in applications where incorrect placements could negatively affect network performance.

**Recall:** The recall values reveal how effectively each model identifies all actual positive cases. The RNN model shows a recall of 0.89, while CNN lags behind at 0.70, indicating it misses a significant number of true positives. The Improved RNN improves upon the basic RNN with a recall of 0.93. Both Bidirectional LSTM and LSTM with Attention surpass all previous models, achieving a recall of 0.97. This suggests that these two architectures are highly capable of detecting the majority of optimal router placements.

**F1 Score:** The F1 score, which balances precision and recall, provides a holistic measure of classification performance. RNN and CNN have F1 scores of 0.94 and 0.82 respectively, with the Improved RNN performing better at 0.96. Bidirectional LSTM and LSTM with Attention achieve the highest F1 scores of 0.99, reflecting excellent consistency and robustness in their classification decisions.

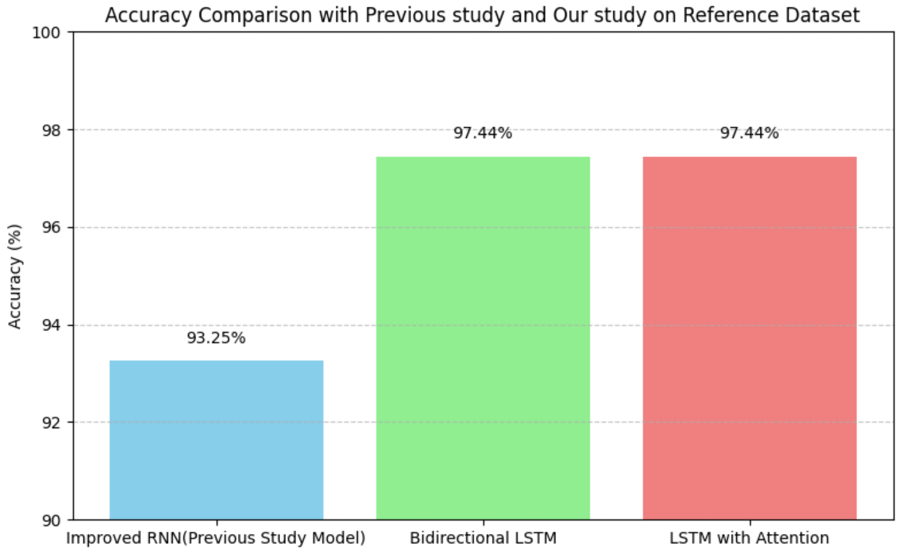


Figure 4.11: Accuracy Comparison with Previous study and Our study on Reference Dataset

Figure 4.11 clearly demonstrates that while the Improved RNN model-proposed in the reference paper delivers high classification performance, the newly implemented Bidirectional LSTM and LSTM with Attention models surpass it across all metrics. With significantly improved recall, F1 score, and overall accuracy. This indicates that the models developed in this study not only match but exceed the performance of the baseline Improved RNN.

### 4.3.3 Results on Real-World Collected Dataset

Models were evaluated with help of regression metrics (RMSE, MAE, MSE, $R^2$) and classification metrics (Accuracy, Precision, Recall, F1-score) with a 6.5-meter threshold. Below are the results.

Table 4.3: Previous study Results on Reference dataset

| **Model** | **Accuracy (%)** | **Precision** | **Recall** | **F1 Score** |
|---|---|---|---|---|
| RNN | 88.61 ± 5.47 | 1.00 ± 0.00 | 0.89 ± 0.05 | 0.94 ± 0.03 |
| CNN | 69.54 ± 7.38 | 1.00 ± 0.00 | 0.70 ± 0.07 | 0.82 ± 0.05 |
| Improved RNN | **93.25 ± 6.10** | 1.00 ± 0.00 | 0.93 ± 0.06 | 0.96 ± 0.03 |

Table 4.4: Our study Results on Real-World Collected Dataset

| **Model** | **Accuracy (%)** | **Precision** | **Recall** | **F1 Score** |
|---|---|---|---|---|
| Conv1D+Bi-LSTM+Dense | **95.89 ± 0.00** | 1.00 ± 0.00 | 0.96 ± 0.00 | 0.98 ± 0.00 |
| Bidirectional LSTM | **95.89 ± 0.00** | 1.00 ± 0.00 | 0.96 ± 0.00 | 0.98 ± 0.00 |
| GRU | **98.63 ± 0.00** | 1.00 ± 0.00 | 0.99 ± 0.00 | 0.99 ± 0.00 |
| LSTM with Attention | **98.63 ± 0.00** | 1.00 ± 0.00 | 0.99 ± 0.00 | 0.99 ± 0.00 |

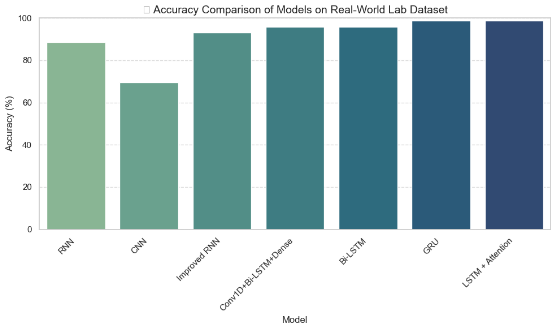


Figure 4.12: Accuracy Comparison of Models

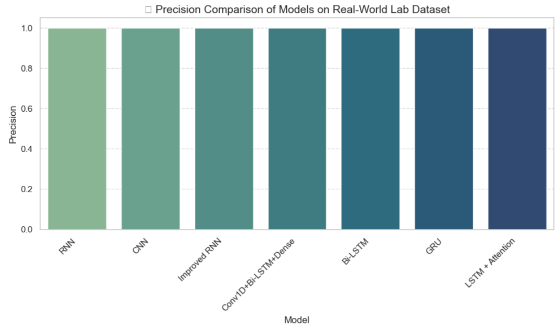


Figure 4.13: Precision Comparison of Models

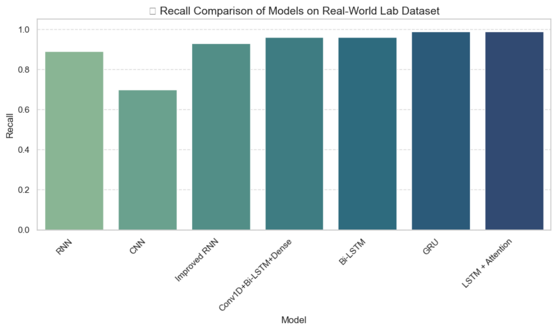


Figure 4.14: Recall Comparison of Models

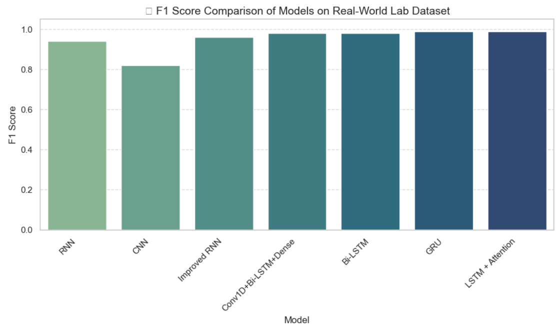


Figure 4.15: F1 Score Comparison of Models

### 4.3.4 Interpretation of Previous study(on Reference Dataset) and Our study (on Collected Dataset) Results

**Accuracy:** In terms of classification accuracy, the CNN model performs the weakest (69.54% ± 7.38%), while the RNN improves to 88.61% ± 5.47%, and the Improved RNN shows further enhancement at 93.25% ± 6.10%. The Conv1D+Bi-LSTM+Dense and Bidirectional LSTM models both achieve 95.89% ± 0.00%, whereas the GRU and LSTM with Attention models reach the highest accuracy at 98.63% ± 0.00%, demonstrating not only improved performance but also greater stability.

**Precision:** All models presented a perfect precision score of 1.00 ± 0.00, indicating that they accurately identify positive instances (i.e., optimal router placements) without producing any false positives. This consistency across all models confirms their reliability in distinguishing correct placement zones.

**Recall:** Recall values reflect each model's ability to capture all actual positive cases. The CNN model reports the lowest recall of 0.70 ± 0.07, suggesting it misses a significant number of true positives. The RNN model improves upon this with 0.89 ± 0.05, while the Improved RNN achieves a recall of 0.93 ± 0.06. More advanced models, such as Conv1D+Bi-LSTM+Dense, Bidirectional LSTM, GRU, and LSTM with Attention, attain higher recall values ranging from 0.96 ± 0.00 to 0.99 ± 0.00, indicating their superior performance in correctly identifying optimal placements.

**F1 Score:** The F1 score provides a balanced measure of precision and recall. The CNN model records the lowest F1 score of 0.82 ± 0.05, followed by the RNN with 0.94 ± 0.03. The Improved RNN offers a better balance with an F1 score of 0.96 ± 0.03. The highest F1 scores are achieved by the GRU and LSTM with Attention models (0.99 ± 0.00), reflecting their strong ability to maintain both precision and recall.

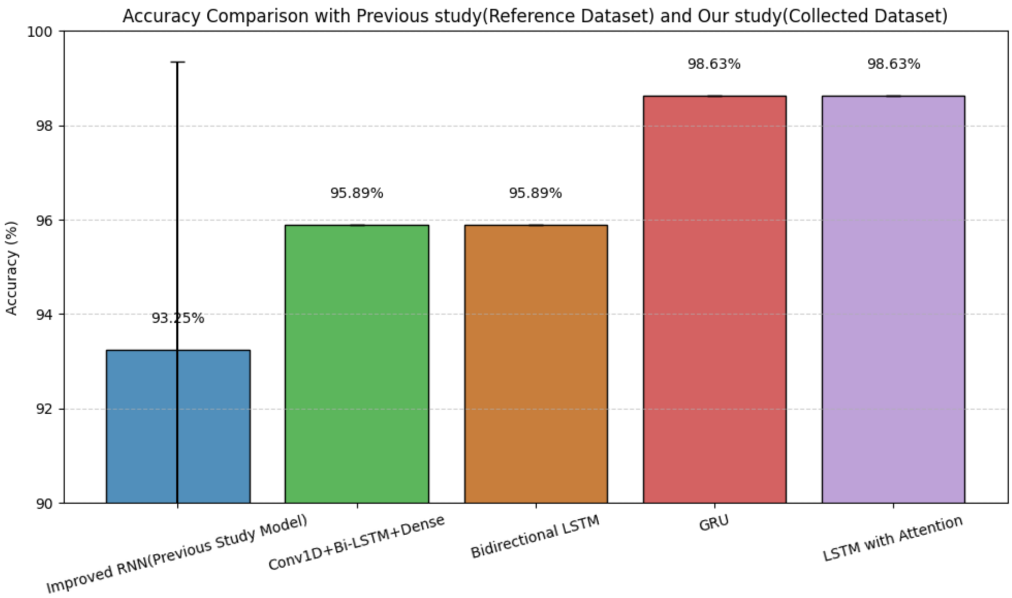


Figure 4.16: Accuracy Comparison with Previous study(Reference Dataset) and Our study(Collected Dataset)

Figure 4.16 illustrates that although the Improved RNN from the reference study demonstrates solid classification capabilities, the proposed models—especially GRU and LSTM with Attention—consistently surpass it across all evaluation metrics on the collected dataset.

## 4.4 Coordinate Prediction Analysis

### 4.4.1 Graph Explanation

**Axes**: The X and Y axes represent the spatial coordinates, with X ranging from 0 to 20 and Y from 0 to 12, depending on the dataset (collected or reference).

**Data Points**:

- Blue Dots (True Coordinates): These points depict the actual coordinates from the dataset, acting as the benchmark to assess the performance of various models.
- Green Dots (Predicted Coordinates – Models): These points illustrate the coordinates predicted by different models (Bi-LSTM, GRU, LSTM + Attention, Conv1D + Bi-LSTM). They reflect the models' capability to approximate the true positions.

- Red X (Best Signal – Predicted): This marker highlights the predicted coordinate with the best signal strength for each model.
- Black Circle (Best Signal – True): This marker indicates the true coordinate with the best signal strength, serving as a reference for the predicted best signal.

### 4.4.2 Reference Dataset

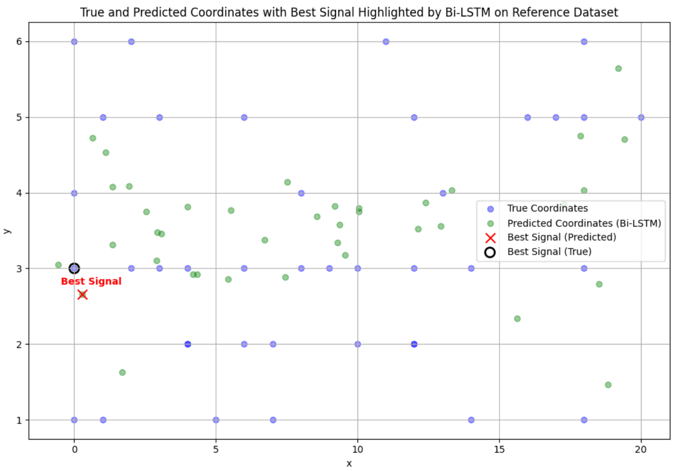


Figure 4.17: True and Predicted Coordinates by Bi-LSTM on Reference dataset

Figure 4.17 illustrates the true and predicted coordinates produced by the Bi-LSTM model on the reference dataset. The predicted best signal (red X) closely aligns with the actual best signal (black circle), demonstrating strong prediction accuracy at that location. Most data points are distributed along the x-axis from 0 to 20 and concentrated between y-values of 2 to 6.

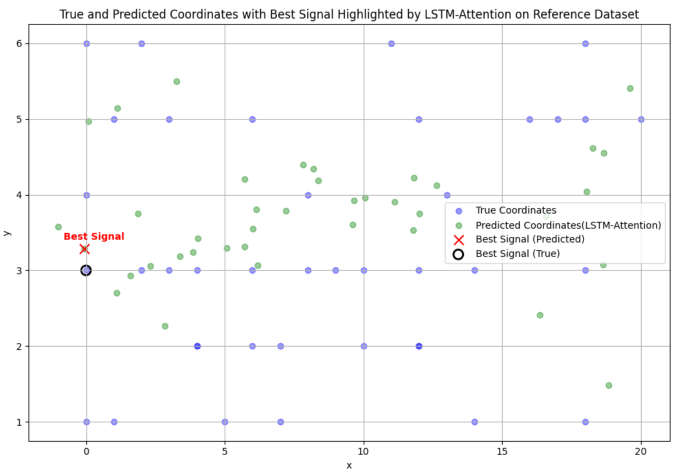


Figure 4.18: True and Predicted Coordinates by Bi-LSTM + Attention on Reference dataset

Figure 4.18 shows the true and predicted coordinates generated by the LSTM-Attention model on the reference dataset. The predicted best signal (red X) closely matches the actual best signal (black circle) near (2, 3), demonstrating precise estimation for that point. Most data points are concentrated between x-values of 0 to 20 and y-values of 2 to 6.

### 4.4.3 Real-World Collected Dataset

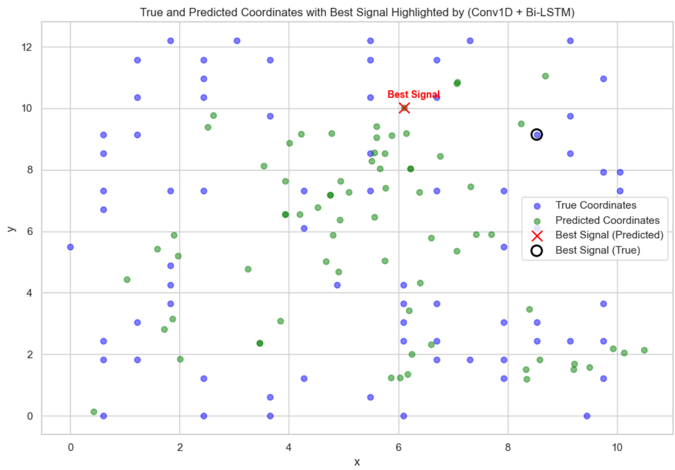


Figure 4.19: True and Predicted Coordinates by (Conv1D + Bi-LSTM) on collected Dataset

Figure 4.19 presents the actual and predicted coordinates from the Conv1D + Bi-LSTM model applied to the collected dataset. The predicted best signal (red X) closely aligns with the actual best signal (black circle) near (8, 10), reflecting strong accuracy at that point. Data points are generally distributed across the full plot range, especially between x = 0–10 and y = 0–10.

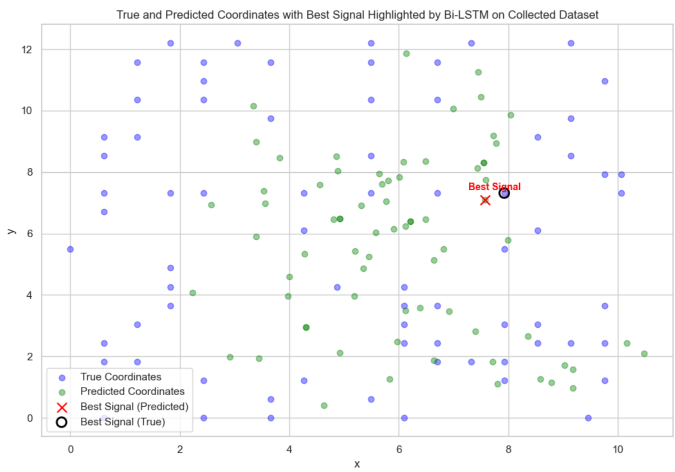


Figure 4.20: True and Predicted Coordinates by Bi-LSTM on Collected Dataset

Figure 4.20 visualizes the actual and predicted coordinates using the Bi-direction LSTM model on the collected dataset.The predicted best signal (red X) closely matches the actual best signal (black circle) near (8, 7), suggesting strong accuracy for that key point. Data points are broadly spread, with more clustering between x = 0–10 and y = 2–10.


Figure 4.21: True and Predicted Coordinates by GRU on Collected Dataset

Figure 4.21 visualizes true versus predicted coordinates from a GRU model on a collected dataset, highlighting the best signal. The best signal, marked by a black circle (true) and a red X (predicted), is located near (7, 8), demonstrating high prediction accuracy for this point. The distribution of points, concentrated between y-values of 0 to 10 and x-values of 0 to 10, mirrors patterns seen in other models on the same dataset.

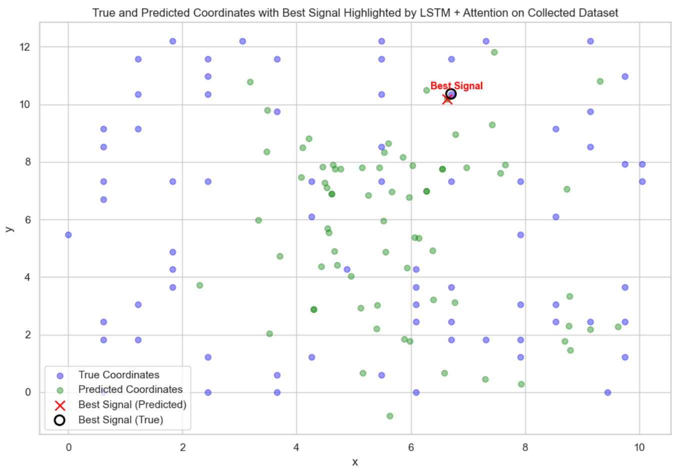


Figure 4.22: True and Predicted Coordinates by Bi-LSTM + Attention on Collected Dataset

Figure 4.22 illustrates the comparison between true and predicted coordinates using an LSTM + Attention model on a collected dataset, with the best signal emphasized. The best signal, indicated by a black circle (true) and a red X (predicted), is positioned near (8, 10), showcasing strong prediction accuracy for this specific point. The points are scattered throughout the range, with a slight clustering between y-values of 0 to 10 and x-values of 0 to 10, aligning with trends observed in other models on the same dataset.

### 4.4.4 Evaluation on External Real-World Collected Test Set

To further validate the generalization capability of the trained models, an independent external test set consisting of seven reference point was introduced. This small dataset was collected separately from the main training and testing data but shares the same characteristics, including RSSI values from six access points (AP1 to AP6) and the corresponding actual X, Y, and Z coordinates. The RSSI values within this test set range from $-45$ to $-78$ dBm, consistent with the primary real-world dataset, indicating a similar indoor environment and signal propagation conditions.

Although limited in size, this external dataset plays a critical role in assessing the real-world applicability of the models. It allows an examination of the models' behavior when exposed to previously unseen data—mirroring practical scenarios where environmental dynamics, interference, and slight signal variations could influence localization performance. All seven reference points were reshaped into a (7, 3, 2) format to temporal input requirements of the proposed deep learning architectures, including RNN, GRU, LSTM, Bi-LSTM, LSTM with Attention, and Stacked LSTM.

#### 4.4.4.1 Actual External Test Set Values

Table 4.5 shows the actual values of the RSSI readings and corresponding true coordinates for the seven external sample points.

Table 4.5: Actual RSSI and Coordinates in External Test Set

| Sample | AP1 | AP2 | AP3 | AP4 | AP5 | AP6 | X (m) | Y (m) | Z (m) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | -62 | -65 | -73 | -78 | -60 | -57 | 6.096 | 0.6096 | 4.572 |
| 2 | -70 | -65 | -68 | -69 | -68 | -45 | 6.7056 | 0.6096 | 4.572 |
| 3 | -58 | -65 | -69 | -72 | -66 | -47 | 7.3152 | 0.6096 | 4.572 |
| 4 | -58 | -65 | -69 | -73 | -66 | -46 | 7.9248 | 0.6096 | 4.572 |
| 5 | -65 | -67 | -65 | -73 | -63 | -57 | 8.5344 | 0.6096 | 4.572 |
| 6 | -75 | -68 | -70 | -75 | -64 | -54 | 9.1440 | 0.6096 | 4.572 |
| 7 | -75 | -68 | -72 | -78 | -65 | -53 | 9.7536 | 0.6096 | 4.572 |

#### 4.4.4.2 Predicted Coordinates by Trained Models

Table 4.6: Predicted Coordinates on External Test Set

| Model | X Predictions (m) | Y Predictions (m) | Z Predictions (m) |
|---|---|---|---|
| GRU | 4.1037, 8.4446, 6.7968, 7.2030, 4.7958, 5.9607, 6.5508 | 4.0559, 1.6814, 1.4840, 1.5303, 5.3050, 4.5617, 3.8942 | 4.6599, 4.3799, 4.3310, 4.3137, 4.6345, 4.5736, 4.5378 |
| Bi-LSTM | 4.2518, 8.7344, 6.5001, 6.8049, 5.2909, 7.0403, 7.4298 | 2.1184, 1.6944, 1.2109, 1.1483, 3.6943, 3.2158, 2.3636 | 4.7066, 4.5096, 4.8168, 4.8241, 4.5649, 4.5725, 4.5632 |
| LSTM + Attention | 4.4681, 8.8488, 8.1536, 8.4653, 4.1100, 5.3085, 6.2217 | 3.5021, 1.3900, 0.9891, 1.0096, 4.6656, 3.8782, 3.1042 | 4.6133, 4.6019, 4.6001, 4.6051, 4.6030, 4.6043, 4.5936 |
| Conv1D+Bi-LSTM | 4.5692, 4.4612, 4.5765, 4.5777, 4.5830, 4.5610, 4.5581 | 3.2600, 9.4836, 6.8066, 6.8879, 5.0874, 7.2903, 7.7694 | 2.3260, 1.6939, 1.4877, 1.4069, 5.0169, 3.1835, 1.7578 |

The trained models, which were optimized using the collected dataset, were then predict X, Y, and Z coordinates for each of these seven test points. Table 4.6 presents the predicted results across all models.

### 4.4.5 Summary of Results and Simulation

The experimental evaluation conducted on both the reference and collected datasets demonstrates significant performance improvements over the baseline Improved RNN model. On the reference dataset, the Bidirectional LSTM and LSTM with Attention models achieved the highest accuracy of 97.44%, surpassing the Improved RNN's accuracy of 93.25%. These models also recorded higher recall and F1 scores, indicating superior generalization and balanced classification performance.

On the collected dataset, the performance gap widened further. The GRU and LSTM with Attention models achieved an outstanding accuracy of 98.63%, with precision, recall, and F1 scores reaching 1.00 or very close. These results clearly outperform the Improved RNN, which attained an accuracy of 93.25% on the reference dataset and is used as the baseline model.

**In summary**, while the Improved RNN served as a strong benchmark, the proposed deep learning models—particularly GRU and LSTM with Attention—consistently delivered enhanced classification metrics.

# Chapter 5

# Real-World Scenarios and Use Cases

The optimization of router placement in indoor environments is a critical challenge in modern wireless networking, especially as the demand for seamless connectivity continues to grow with the proliferation of smart devices and Wi-Fi 6 technologies. Traditional methods, often reliant on manual configurations or heuristic rules, struggle to adapt to the dynamic and complex nature of indoor spaces, where factors like walls, furniture, and human movement significantly impact signal propagation [19] [20]. This chapter explores real-world scenarios and practical use cases where deep learning models can enhance signal coverage and performance by intelligently optimizing router placement, drawing on recent advancements in the field [1] [21].

## 5.1 Real-World Scenarios for Router Placement Optimization

Indoor environments such as offices, homes, and commercial buildings present unique challenges for wireless signal coverage due to structural diversity and dynamic conditions. Deep learning models—particularly those leveraging Recurrent Neural Networks (RNNs) and variants like Long Short-Term Memory (LSTM) units—have shown promise in learning spatial and temporal patterns in Received Signal Strength Indicator (RSSI) data [21] [2] [14].

### 5.1.1 Smart Offices with High Device Density

Modern smart offices contain high densities of Wi-Fi-enabled devices, including laptops, smartphones, and IoT sensors. Deep learning models such as LSTM can learn RSSI patterns in these environments and recommend optimal router placements [14] [3]. Strategic placement using these models ensures reduced interference and consistent signal quality. By training on dense device activity data, these models can proactively allocate routers to high-demand areas like conference rooms, maintaining connectivity during video conferencing or collaborative work sessions [5] [12].

### 5.1.2 Residential Settings with Structural Complexity

Homes have irregular layouts with multiple floors, walls, and obstacles that hinder signal propagation. Deep learning architectures like Conv1D-LSTM can analyze spatial RSSI variations and determine ideal router positions [17] [8]. These models learn the signal weakening patterns across rooms, providing configurations that ensure whole-home coverage. For instance, rather than positioning the router in a utility room, the model might recommend a central stairwell to maximize coverage to all floors simultaneously [2].

### 5.1.3 Commercial Spaces with Dynamic User Movement

High-mobility environments such as airports or malls require adaptive router placement strategies. Hybrid models combining deep learning and reinforcement learning can respond to real-time RSSI changes and dynamic user behaviors. These systems adaptively relocate or reconfigure access points for consistent coverage in high-traffic areas like waiting zones or food courts. As demonstrated in [7] [12], this approach ensures minimal packet loss and improved user experience in time-sensitive applications like navigation or mobile ticketing.

## 5.2 Use Cases of Deep Learning in Router Placement Optimization

Applications of these models extend across various sectors, showcasing their practical utility.

### 5.2.1 Enhancing Connectivity in Educational Institutions

University campuses often span large areas with thousands of users connecting simultaneously. Traditional setups often result in overloaded access points and dead zones. Deep learning models such as Bi-LSTM can guide AP deployment in classrooms, libraries, and student lounges [16] [18]. For instance, placing routers near lecture podiums or collaborative zones based on temporal usage data can maintain performance even during peak periods, directly impacting digital learning continuity [10].

### 5.2.2 Improving Network Performance in Healthcare Facilities

Wi-Fi reliability is critical in hospitals where medical devices rely on real-time connectivity. LSTM models with attention mechanisms can prioritize RSSI data from high-priority areas like ICUs and ERs, guiding access point placement accordingly [6]. By maintaining strong signals in these zones, healthcare operations become more efficient, supporting applications such as patient monitoring and digital health records [1].

### 5.2.3 Optimizing Signal Coverage in Industrial Warehouses

Warehouses feature extensive obstructions from shelves, machinery, and metallic surfaces. Deep learning models such as Conv1D-LSTM are effective in processing sequential RSSI data to recommend optimal AP locations that ensure smooth communication among Automated Guided Vehicles (AGVs) and IoT nodes [21] [13]. Deploying routers at higher elevations and at central aisle points—as learned by these models—enables real-time tracking and smooth logistics operations [2].

## 5.3 Challenges and Considerations in Real-World Deployment

Despite their promise, deep learning-based router placement systems face challenges. RSSI readings are sensitive to noise, interference, and user dynamics, requiring frequent model updates and calibration [20]. Models like Transformers or stacked Bi-LSTM are computationally expensive, complicating their deployment in embedded or edge-based environments [9]. Additionally, integrating such intelligent systems within existing Wi-Fi infrastructure must address compatibility with IEEE 802.11ax protocols and respect user data privacy during RSSI data collection [4].

## 5.4 Future Implications

The rapid evolution of wireless standards like Wi-Fi 6 and 6E demands adaptive infrastructure solutions. Deep learning, when integrated with reinforcement learning, enables autonomous, self-optimizing Wi-Fi deployments [3]. These systems are expected to play a central role in smart buildings, IoT networks, and public infrastructure, ensuring optimized and resilient wireless access. As devices and bandwidth demands increase, intelligent router placement will be essential for ensuring efficient, scalable, and user-centric network experiences [1][2].

# Chapter 6

# Conclusion and Future Work

## Conclusion

This research investigated the use of advanced deep learning models for indoor localization and optimal router placement based on Wi-Fi RSSI data. Deep learning architectures were implemented and evaluated using both a publicly available reference dataset and a collected real-world dataset in a laboratory environment. The experimental results provide important insights into the effectiveness and adaptability of various models under different data conditions.

On the **reference dataset**, the Bidirectional LSTM and LSTM with Attention models achieved the highest performance, with each reaching an accuracy of 97.44% and F1 scores of 0.99. These outcomes represent a notable improvement compared to the baseline Improved RNN, which recorded 93.25% accuracy. The findings highlight the advantages of integrating bidirectional processing and attention mechanisms, which enhance the model's ability to capture spatial dependencies and accurately determine optimal router placements.

On the **real-world collected dataset**, the GRU and LSTM with Attention models achieved the highest performance, each reaching an accuracy of 98.63% and F1 scores close to 1.00. These models exhibited a notable improvement over the baseline Improved RNN, which recorded an accuracy of 93.25%. The findings highlight the effectiveness of temporal sequence learning in GRU and the attention mechanism's ability to enhance focus on relevant features, enabling robust prediction even under complex indoor conditions.

In **summary**, the advanced deep learning architectures—namely GRU, Bidirectional LSTM, and LSTM with Attention—consistently demonstrated superior performance compared to the Improved RNN across both the reference and real-world datasets. Their strong generalization on structured data and robustness under real-world variability highlight their effectiveness for deployment in smart indoor environments. These models present viable solutions for key applications such as router positioning, signal enhancement, and user localization, paving the way for more efficient and intelligent wireless network systems.

Despite these achievements, there remain some **research gaps and opportunities for future work**. The current study assumes a static environment without accounting for dynamic elements like moving objects, people, or changing layouts, which can influence signal propagation. Additionally, the dataset size—especially the real-world samples—was relatively small, which may limit generalizability to larger-scale environments. Future research could experiment with the integration of reinforcement learning for adaptive router repositioning, expand the dataset with more spatial diversity, and investigate hybrid models combining deep learning with physical signal propagation models. Real-time implementation and deployment in live environments would also validate the feasibility of these models beyond offline simulations.

# Bibliography


[1] Tarek Alhmiedat, Mohammed Abualhaj, and Raad Al-Sayyed. “Optimization of WiFi 6 Deployment in Smart Environments: A Case Study of Multi-Service Networks”. In: *Journal of Communications and Networks* 25.1 (2023), pp. 80–89.

[2] Tarek Alhmiedat, Mohammed Abualhaj, and Amr Youssef. “A fingerprint-based localization approach for wireless sensor networks using machine learning models”. In: *IEEE Access* 11 (2023), pp. 105123–105135.

[3] Tarek Alhmiedat and Robert Istepanian. “Enhancing Signal Coverage and Performance for Router Placement Using Deep Learning Model”. In: *Wireless Networks* (2024). In press.

[4] Hyeonjoong Chung et al. “Optimization of WiFi 6 Deployment in Smart Environments”. In: *Journal of Communications and Networks* 23.2 (2021), pp. 140–150. DOI: 10.1109/JCN.2021.000019.

[5] Rui He et al. “WiFi-based device-free passive localization with deep learning”. In: *IEEE Transactions on Vehicular Technology* 70.5 (2021), pp. 4234–4245.

[6] Md Sazzad Hossain and Ghulam Muhammad. “Deep Learning for Indoor Localization”. In: *IEEE Communications Letters* 24.4 (2020), pp. 829–832. DOI: 10.1109/LCOMM.2020.2967386.

[7] Omar Al-Jarrah, Esam Al-Haj, and Mohammad S Obaidat. “AI-driven wireless network optimization: Challenges and opportunities”. In: *IEEE Systems Journal* 17.1 (2023), pp. 400–409.

[8] Jin Kim, Donghee Park, and Sunghyun Choi. “Wi-Fi based indoor localization using deep learning and CNN with trajectory CSI data”. In: *Sensors* 21.14 (2021), p. 4766.

[9] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. “Deep learning”. In: *Nature* 521.7553 (2015), pp. 436–444. DOI: 10.1038/nature14539.

[10] Hao Liu et al. “Wi-Fi Based Indoor Localization Using Deep Learning and CNN”. In: *IEEE Sensors Journal* (2020). DOI: 10.1109/JSEN.2020.2976978.

[11] Xuan Meng et al. “A survey on deep learning for localization and mapping: Towards the age of spatial machine intelligence”. In: *IEEE Transactions on Intelligent Transportation Systems* 22.3 (2020), pp. 1341–1360.

[12] Mohammad Mohammadi et al. “AI-Driven Wireless Network Optimization: Challenges and Opportunities”. In: *IEEE Network* 35.6 (2021), pp. 264–271. DOI: 10.1109/MNET.011.2000613.

[13] Ameer Mohammed, Sadik Gharghan, and Ali M Jawad. “A real-time fingerprint-based indoor positioning using deep learning”. In: *IEEE Access* 10 (2022), pp. 16310–16320.

[14] Avinash Singh, A. L. Sangal, and Rajneesh Rani. “Enhancing Signal Coverage and Performance for Router Placement Using Deep Learning Model”. In: Department of Computer Science and Engineering. Jalandhar, India, 2024.

[15] Joaquín Torres-Sospedra et al. “UJIIndoorLoc: A new multi-building and multi-floor database for WLAN fingerprint-based indoor localization”. In: *2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2015, pp. 1–6.

[16] Xiao Wang et al. “A Survey on Deep Learning-Based Localization”. In: *ACM Computing Surveys* 52.1 (2020). DOI: 10.1145/3299096.

[17] Yifan Wu et al. “Deep learning for indoor localization using Wi-Fi signal fingerprints”. In: *IEEE Sensors Journal* 23.6 (2023), pp. 7801–7811.

[18] Wei Xu, Bing Liu, and Ming Chen. “LSTM-based indoor localization with transfer learning”. In: *Sensors* 21.11 (2021), p. 3754.

[19] Mohamad Yassin et al. “Recent advances in indoor localization: A survey on theoretical approaches and applications”. In: *IEEE Communications Surveys & Tutorials* 19.2 (2017), pp. 1327–1346.

[20] Faheem Zafari et al. “A Survey of Indoor Localization Systems and Technologies”. In: *IEEE Communications Surveys & Tutorials* 21.3 (2019), pp. 2568–2599. DOI: 10.1109/COMST.2019.2911558.

[21] Lin Zhang, Min Li, and Jun Wang. “Recurrent neural networks for accurate RSSI indoor localization”. In: *Neurocomputing* 405 (2020), pp. 20–29.