# RS-DeepNet: A Machine Learning Aided RSSI Fingerprinting for Precise Indoor Localization

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***Abstract*—Intelligent recommendation applications in smart cities require the precise location of the users. The traditional global positioning system (GPS) uses satellite signals for the precise positioning of the user but is vulnerable to signal blockage in the complex indoor environment. The unforeseeable propagation losses due to multi-path effects as well as the permittivity and permeability difference of the materials lead to non-linear attenuation in the electromagnetic (EM) beam generated by the beacon devices in the indoor environment. Therefore, a robust indoor localization algorithm is required to precisely localize the users in the indoor environment with severe EM blockages. In this paper, we propose a novel hybrid RS-DeepNet framework that uses received signal strength (RSS) from WiFi devices for indoor localization of users. The proposed RS-DeepNet is a deep learning architecture that utilizes multiple gated recurrent layers (GRU) and a K-nearest neighbors (KNN) classifier to estimate the precise location of the user in the indoor setup. Simulation results show that the proposed RS-DeepNet outperforms the state-of-the-art approaches and efficiently localizes the users in two indoor scenarios and achieves a lowest mean absolute error of 4.81 and 1.68 meters, respectively.**

***Index Terms*—Indoor localization, machine learning, RSSI fingerprinting, feature extraction, classification**

## I. Introduction

Most of the internet users in the network are located in the indoor environment, therefore, network densification is considered to provide service to these users by deploying a user-centric small base station deployment in the indoor setup [1], [2]. Acquiring the accurate position information of the users is critical to enable different location-based services in the indoor environment [3]. The global navigation satellite system (GNSS) is capable of localizing the user and can achieve a sub-meter localization accuracy in some scenarios. However, it does not perform well in the indoor setup [4]. Visual-based localization (VBL) and wireless sensor-based localization (WSBL) use computer vision and wireless sensor network (WSN) for precise indoor localization [5]. However, visual biometric-based localization of individuals through indoor CCTV cameras suffers from various photometric variations such as intra-class occlusions, illumination differences, scale variations, and orientation changes [6]. The WSBL is broadly classified into time-based, angle-based, and receive-power-based techniques [7]. The time-based indoor localization relies on the time of arrival (ToA), time difference of arrival (TDoA), and round trip time (RTT), while the angle-based method relies on the radio signal's angle of arrival (AoA) at a specified grid of location coordinates and the receive-power-based methods depend on the received signal strength (RSS) fingerprint and the radio propagation model of the environments. The RSS fingerprint consists of the received signal power from the anchor nodes at uniformly distributed grid locations and carries useful location information. Fingerprint includes an RSS indicator (RSSI) and is directly accessed from the application layer without requiring extra hardware or software changes. However, a huge fingerprint data transmission is needed in fingerprint-based localization, which makes it inefficient in terms of power, memory, and computational resources, especially in complex environments [8].

The emerging Internet-of-Things (IoT) sensor technology and the advancement in artificial intelligence (AI) have recently captured the attention of researchers to develop an intelligent and efficient indoor localization framework for smart cities. Machine learning (ML) techniques are capable of tackling the challenges related to indoor localization. The ML model either utilizes the raw RSSI data or extracts statistical features from the input data. The classification frameworks utilized for indoor localization so far include the multi-class support vector machine (SVM) [9], K-nearest neighbors (KNN) [10], probabilistic decision tree, and ensemble models. However, these models result in lower precision and higher mean absolute error (MAE). The deep neural network (DNN) comprising long-short term memory (LSTM) [11], bi-directional LSTM (BiLSTM) [12], and one-dimensional convolutional neural network (1D-CNN) [13] are used to accurately determine the indoor object's location based on the RSS from beacon nodes. ML frameworks also utilize the AoA and TDoA data for low-cost indoor positioning. Instead of raw data by the statistical handcrafted methods, a DNN generates the distinctive feature values for the raw input data and results in improved localization performance. The authors in [13] transformed the RSSI fingerprint data into two-dimensional (2D) images using Continuous Wavelet Transforms (CWT) and applied DNN models to estimate indoor object coordinates. Although the 2D DNN is robust against photometric noises, the limited number of beacons

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and the limited difference in RSSI signal strengths within the fingerprint result in lower precision compared to 1D CNN models.

Unlike isolated feature extraction and classification models, fused frameworks are utilized, including multiple ML algorithms to combine and localize indoor objects. The Unsupervised Fusion of Extended Candidate Location Set (UFL-ECLS) [14] is a fused model consisting of multiple trained classifiers. However, the performance of UFL-ECLS is highly dependent on the individual classifier accuracy, and misclassification of a single classifier could lead to degradation in the overall localization performance. To address this issue, the authors in [15] propose a SmartLoc framework that utilizes multiple ML algorithms along with alignment probabilistic procedures to enhance offline training processes. The SmartLoc framework offers greater precision by employing multiple ML frameworks and probabilistic alignment methods However, it suffers from the increased computational cost issue, which makes it unsuitable for real-time applications.

Motivated by the aforementioned works, the goal of this paper is to propose an efficient ML framework for precise indoor localization that utilizes RSSI fingerprint data to estimate the location coordinates of the users in the complex indoor environment. The existing frameworks for indoor localization need more accuracy, which is attributed either to the vulnerability of the estimation model or the limitations of training samples for the model. To address this issue and achieve high accuracy while reducing computational complexity, this paper proposes RS-DeepNet, which leverages the advantages of both DNN features and clustering by first extracting features from the RSSI data and then using these features for clustering-based classification.

The main contributions of the paper are outlined as follows.

- We propose an RS-DeepNet which is a DNN architecture for indoor localization. The proposed framework is based on feature extraction from the input RSSI data followed by an isolated classification of location information from the extracted features. The feature extraction is performed using multiple cascaded GRU blocks, each comprising a GRU layer, normalization layer, and dropout layer. The isolated KNN classifier is used to classify the deep features collected through the cascaded GRU-DNN to estimate the user's coordinates in order to achieve highly precise localization.
- Considering two different indoor scenarios, we demonstrate that the proposed RS-DeepNet precisely predicts the user location information from the RSSI fingerprint data. We further show that the proposed learning framework outperforms the other existing techniques by achieving the lowest mean absolute error (MAE).

The rest of the paper is organized as follows: Section II presents the system model followed by the procedure for generating fingerprint data. Section III presents the methodology of the proposed feature extraction and classification. Section IV provides the simulation results and comparison of the proposed framework with the existing benchmark. Finally, Section V summarizes the key findings and concludes the paper.

## II. System Model

The considered system model has $K'$ number of WiFi access points (APs) with the known location distributed over a square area of dimension $S \times S$. The location coordinate of the $i$th reference user point (UP) is denoted by $\mathcal{U}_i = (x_i, y_i)\ \forall i = \{1, 2, ..N\}$, where $N$ is the number of indoor user equipments. The RSSI-fingerprint-based indoor localization framework consists of an offline training stage and an online testing process. During the offline training stage, the RSSI fingerprint is created by dividing the serving area into a square grid with grid markers across the x and y-axis, respectively. In this study, we consider two indoor environment scenarios as shown in Fig. 1 (a) and (b), respectively. For scenario 1: $S = 30$ m with $K' = 4$ number of distributed APs while for scenario 2: $S = 50$ m with $K' = 5$ number of distributed APs. The UPs are distributed across the grid points in such a way that each grid position belongs to one UP.

The RSSI fingerprint is collected and stored in the database for the particular scenario. The RSSI fingerprint and the location information stored are given by

$$\begin{aligned}\Omega &= \begin{bmatrix}\mathcal{U} & \mathbf{\Psi}\end{bmatrix} \\ &= \begin{bmatrix} (x_i, y_i) & (\Psi_{i,1}, \Psi_{i,2}, ...\Psi_{i,K}) \\ : & : \\ (x_N, y_N) & (\Psi_{i,1}, \Psi_{i,2}, ...\Psi_{N,K}) \end{bmatrix},\end{aligned} \tag{1}$$

where the $\Psi_{n,k}$ refers to RSSI at the $n$th location across the grid received from the $k$th AP.

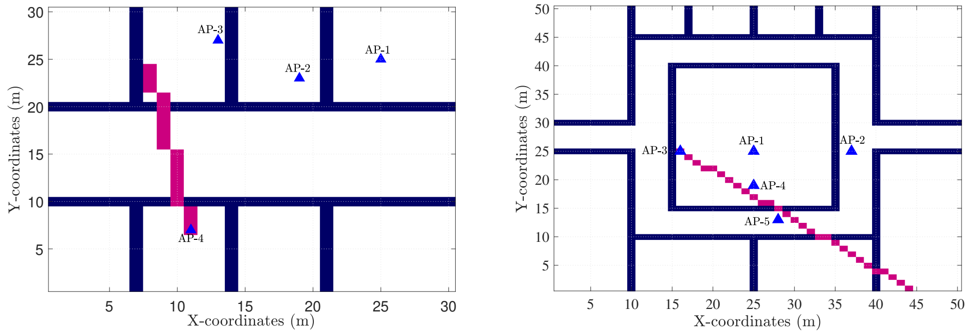
The signal propagating between the $k$th AP and the $n$th UP follows the Log-Normal path loss model and is highly dependent on obstacles within the line-of-sight (LoS) between APs and UPs. In the simulated environment, we consider system-added noise and the random shadowing effect due to the presence of randomly moving objects within the environments [16]. As the RSS randomly fluctuates at each time instant, therefore, the average RSS received from the $k$th AP at location $(x_i, y_i)$ can be expressed as

$$\Psi_{n,k}^t = \frac{\sum_{t=1}^{\mathcal{T}} s_{n,k}(t)}{\mathcal{T}}, \tag{2}$$

where $s_{n,k}(t)$ and $\Psi_{n,k}^t$ denote the RSSI received from the $k$th AP at the $n$th UP and the average RSSI value at time instant $t$, respectively, while $\mathcal{T}$ denotes the total set of time samples.

## III. Proposed DNN architecture for RS-DeepNet

The proposed RS-DeepNet model utilizes GRU DNN for feature extraction from the RSSI fingerprint data and classifies them into the location coordinates of the indoor site. The RSSI fingerprint data, along with the respective geographic location coordinates of the grid is used as a training dataset for the proposed RS-DeepNet. During the online testing the RSSI data is fed into the input of RS-DeepNet to extract the input feature and estimates the nearest locations of the UP. The mean




(a) (b)

Fig. 1: Floor map of RSSI-Fingerprint environment with dark blue represents wall structures while light blue triangle denotes the AP position, and the pink color denotes User trajectory (a) Scenario 1: square grid with $S = 30$m and $K' = 4$ (b) Scenario 2: square grid with $S = 50$m and $K' = 5$.

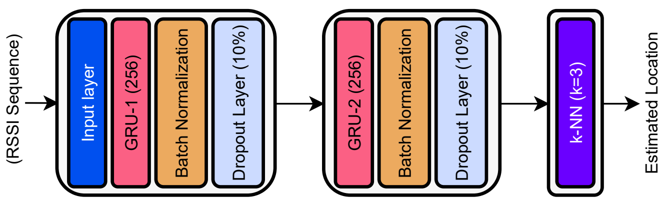



Fig. 2: Proposed RS-DeepNet architecture

location is considered as the position of the test reference UP. As a training dataset, the location coordinates of APs and the RSS fingerprint values of the $k$th AP at $n$th reference UPs are stored in the database and are respectively, given as

$$\mathcal{I} = \mathbf{\Psi} = \begin{bmatrix} (\Psi_{1,1}, \Psi_{1,2}, .., \Psi_{1,K}) \\ (\Psi_{2,1}, \Psi_{2,2}, .., \Psi_{2,K}) \\ \vdots \\ (\Psi_{N,1}, \Psi_{N,2}, .., \Psi_{N,K}) \end{bmatrix}, \tag{3}$$

$$\mathcal{L} = \mathcal{U} = \begin{bmatrix} \mathcal{U}_1 = (x_1, y_1) \\ \vdots \\ \mathcal{U}_N = (x_N, y_N) \end{bmatrix}, \tag{4}$$

where $\mathcal{I}$ represents the Input data and $\mathcal{L}$ is the corresponding labels matrix used during training of the proposed RS-DeepNet architecture.

**RS-DeepNet Architecture:** The proposed RS-DeepNet comprises two GRU blocks followed by an isolated KNN classifier, as shown in Fig. 2. Each GRU block consists of a GRU layer with 256 cell units, a normalization layer, a dropout layer with a probability of 0.1, and $\mathcal{T} = 250$ number of data samples are generated for each indoor scenario. The model is trained with $[\mathcal{I}\ \mathcal{L}]$ accessed from the database. The final output of the proposed RS-DeepNet can be mathematically expressed as

$$\mathcal{O} = \mathcal{C}_{knn}\left(\mathcal{G}_2\left(\mathcal{G}_1\left(\mathcal{I}\right)\right)\right), \tag{5}$$

where $\mathcal{G}_1(\cdot)$, $\mathcal{G}_2(\cdot)$, and $\mathcal{C}_{knn}(\cdot)$ denote the first GRU block, second GRU block, and KNN classifier, respectively. During training, 75% and 25% of the total data are used for training and validation, respectively, while for the KNN classifier $K$ is set to 3. The model is trained for 1000 epochs with a batch size of 64 and a learning rate of 0.005, and an ADAM optimizer is used. Let us denote the actual true locations and the estimated locations of the UPs by $\mathcal{U}$ and $\tilde{\mathcal{U}}$, respectively. Then, the mean absolute error (MAE) can be written as

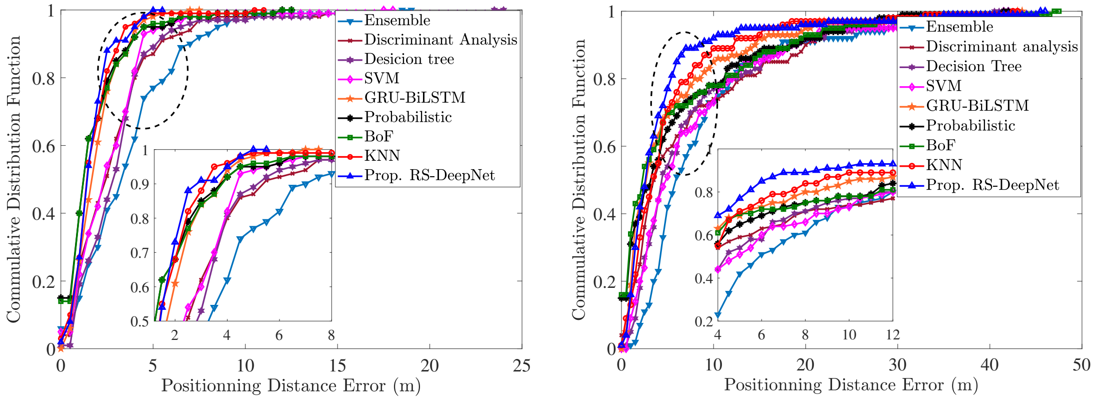
$$\text{MAE} = \frac{1}{\xi_{test}} \sum_{z=1}^{\xi_{test}} |\mathcal{U}_z - \tilde{\mathcal{U}}_z|, \tag{6}$$

where $\xi_{test}$ denotes the total number of test data points considered for evaluation.

## IV. Simulation Results

The performance of the proposed RS-DeepNet model is evaluated in two different simulated virtual environments, as shown in Fig. 1. Both environments have different indoor structures and dimensions. Random environmental noise, path loss, shadowing, and multi-path effects are considered in both environments. We evaluate the performance of the proposed RS-DeepNet in terms of the cumulative distribution function (CDF) of the positioning distance error and the MAE for the tested dataset.

Fig. 3 presents the CDF of the proposed RS-DeepNet in comparison with the other learning techniques for two indoor scenarios. Fig. 3 (a) and (b) show that compared to the traditional models, the proposed RS-DeepNet provide superior performance at lower positioning distance errors for indoor scenario 1 and 2, respectively. The comparison with the other classification models that utilize raw RSSI fingerprints, such as SVM, KNN, decision tree, discriminant analysis, ensemble, and probabilistic models, is also provided. Furthermore, the Bag-of-Features (BoF) method and the stacked GRU-BiLSTM model, which extracts robust features from the raw RSSI, are also considered for a fair comparison. Fig. 3 depicts that the proposed RS-DeepNet achieves superior performance compared to the benchmark methods. The second and third




(a) (b)

Fig. 3: CDF of the positioning distance error (a) Scenario 1 with $S = 30$ (b) Scenario 2 with $S = 50$.

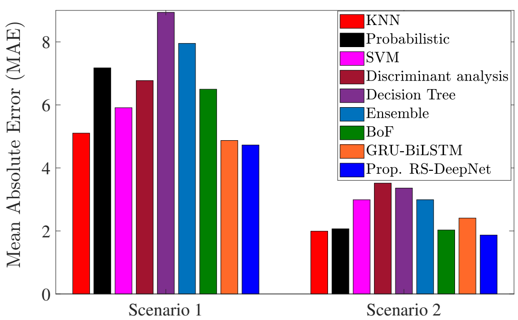



Fig. 4: MAE performance of the proposed RS-DeepNet in comparison with the other DNN models.

best performing indoor localization algorithms are KNN and GRU-BiLSTM, respectively.

Fig. 4 presents the MAE performance of the proposed RS-DeepNet. Fig. 4 depicts that the proposed RS-DeepNet achieves the lowest MAE of 4.81 and 1.68 compared to the other benchmarks in the considered scenario 1 and scenario 2, respectively.

## V. Conclusions

To enable location-based services, the precise localization of the user is critical in the indoor environment. In this regard, this paper proposes a novel RS-DeepNet framework for indoor localization, which is a DNN architecture that utilizes two GRU blocks for feature extraction and an isolated KNN for classification. The proposed RS-DeepNet is tested for two different indoor residential apartment scenarios. It is observed from the simulation results that for both indoor scenarios, the proposed RS-DeepNet precisely estimates the location of UPs and provides superior performance compared to the other DNN models with reduced MAE of 4.81 m and 1.68 m in both indoor scenarios.

## References


[1] Z. H. Abbas, A. Ullah, G. Abbas, F. Muhammad, and F. Y. Li, "Outage probability analysis of user-centric SBS-based HCNets under hybrid Rician/Rayleigh fading," *IEEE Communications Letters*, vol. 24, no. 2, pp. 297–301, 2019.

[2] A. Ullah, Z. H. Abbas, G. Abbas, F. Muhammad, and J.-M. Kang, "Hybrid millimeter wave heterogeneous networks with spatially correlated user equipment," *Digital Communications and Networks*, 2022.

[3] J. Wang, X. Zhang, Q. Gao, H. Yue, and H. Wang, "Device-free wireless localization and activity recognition: A deep learning approach," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 7, pp. 6258–6267, 2016.

[4] X. Guo, L. Li, N. Ansari, and B. Liao, "Knowledge aided adaptive localization via global fusion profile," *IEEE Internet of Things Journal*, vol. 5, no. 2, pp. 1081–1089, 2017.

[5] S. B. Altaf Khattak, M. M. Nasralla, M. A. Esmail, H. Mostafa, and M. Jia, "WLAN RSS-based fingerprinting for indoor localization: A machine learning inspired bag-of-features approach," *Sensors*, vol. 22, no. 14, p. 5236, 2022.

[6] B. Yang, J. Li, and H. Zhang, "Resilient indoor localization system based on UWB and visual-inertial sensors for complex environments," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–14, 2021.

[7] S. M. Asaad and H. S. Maghdid, "A comprehensive review of indoor/outdoor localization solutions in IoT era: Research challenges and future perspectives," *Computer Networks*, p. 109041, 2022.

[8] J. Yan, G. Qi, B. Kang, X. Wu, and H. Liu, "Extreme learning machine for accurate indoor localization using RSSI fingerprints in multifloor environments," *IEEE Internet of Things Journal*, vol. 8, no. 19, pp. 14 623–14 637, 2021.

[9] A. Chriki, H. Touati, and H. Snoussi, "SVM-based indoor localization in wireless sensor networks," in *2017 13th international wireless communications and mobile computing conference (IWCMC)*. IEEE, 2017, pp. 1144–1149.

[10] I. T. Haque and C. Assi, "Profiling-based indoor localization schemes," *IEEE Systems Journal*, vol. 9, no. 1, pp. 76–85, 2013.

[11] Z. Chen, H. Zou, J. Yang, H. Jiang, and L. Xie, "WiFi fingerprinting indoor localization using local feature-based deep LSTM," *IEEE Systems Journal*, vol. 14, no. 2, pp. 3001–3010, 2019.

[12] N. Liu, T. He, S. He, and Q. Niu, "Indoor localization with adaptive signal sequence representations," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 11, pp. 11 678–11 694, 2021.

[13] P. Ssekidde, O. Steven Eyobu, D. S. Han, and T. J. Oyana, "Augmented CWT features for deep learning-based indoor localization using wifi rssi data," *Applied Sciences*, vol. 11, no. 4, p. 1806, 2021.

[14] X. Guo, S. Zhu, L. Li, F. Hu, and N. Ansari, "Accurate WiFi localization by unsupervised fusion of extended candidate location set," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 2476–2485, 2018.

[15] L. Li, X. Guo, and N. Ansari, "Smartloc: Smart wireless indoor localization empowered by machine learning," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 8, pp. 6883–6893, 2019.

[16] M. Jia, S. B. A. Khattak, Q. Guo, X. Gu, and Y. Lin, "Access point optimization for reliable indoor localization systems," *IEEE Transactions on Reliability*, vol. 69, no. 4, pp. 1424–1436, 2019.