A Unified Deep Transfer Learning Model for Accurate IoT Localization in Diverse Environments

University Mohammed VI Polytechnic

Abdullahi Isa Ahmed[1], Yaya Etiabi[1], Ali Waqar Azim[2], and El Mehdi Amhoud[1]

[1]College of Computing, Mohammed VI Polytechnic University (UM6P), Benguerir, Morocco

[2] University of Engineering and Technology, Taxila, Pakistan

College of Computing

Introduction

The recent advancements in the Internet of Things (IoT) have generated significant interest in connecting devices to the internet, reshaping various industries through real-time data collection, object tracking and decision-making processes [1]. IoT facilitates seamless device interaction, data exchange, and continuous data monitoring. Projections estimate that by 2030, there will be about 24.1 billion IoT devices worldwide [2]. A crucial aspect of IoT is localization, which plays a key role in location-based services [3]. The deployment settings for IoT localization, such as indoor (BLE, UWB, RFID, Wi-Fi, VLC), outdoor (GNSS technologies like Galileo, Beidou, GPS), as well as underground, urban, and suburban environments, significantly impact the performance of connected devices [4].

- Existing studies in IoT localization frameworks are environment-specific. Thus, increasing costs, complexity and lack of comprehensive testing across diverse settings affects system generalizability.
- Therefore, there are new demands for low-cost, low-power, long-range technologies like NB-IoT, LTE-M, Sigfox, and LoRaWAN are needed for effective location-based services. Hence, our proposed framework utilizes LoRa (outdoor) and Wi-Fi (indoor).

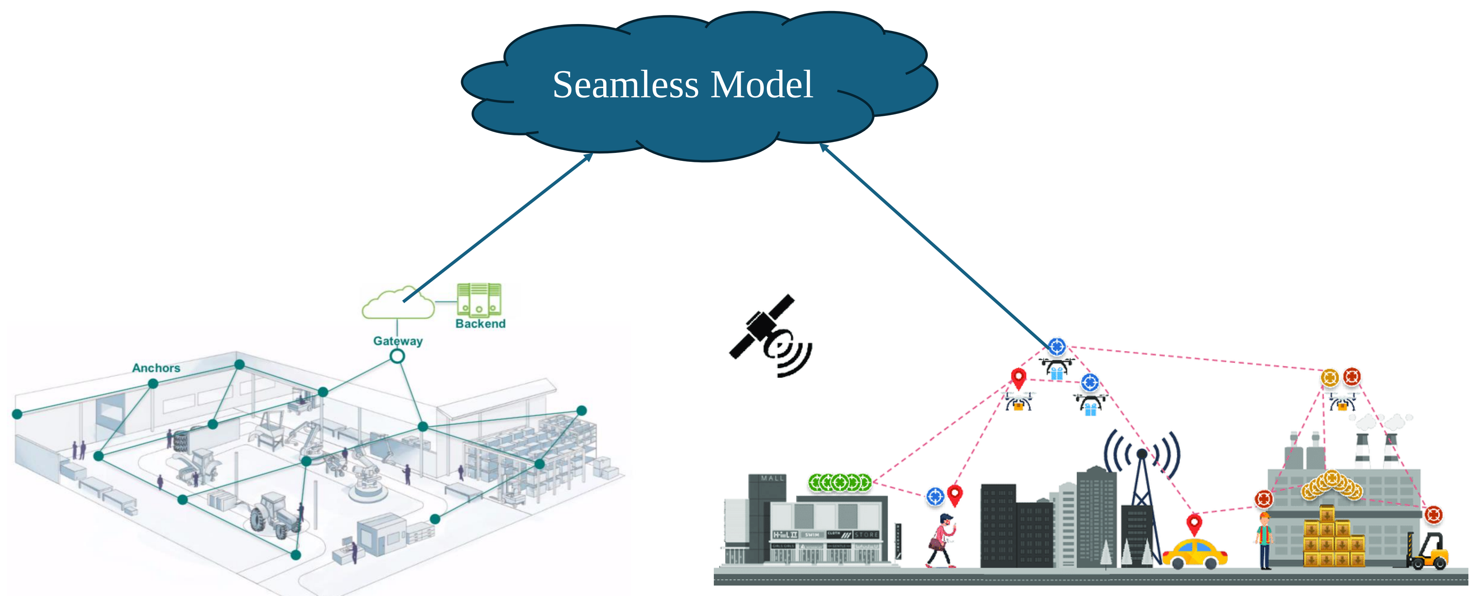

Figure 1: Proposed seamless framework for both indoor and outdoor localization environment

Proposed System Architecture

- In this work, we aim to propose an optimal deep neural network (DNN) framework to predict the estimated location $L \in \{L_0, L_1\}$ and the precise environment $E \in \{0, 1\}$.
- We consider set of received signal strength indicators (RSSI) from both Wi-Fi and LoRa that corresponds $\mathcal{W}$ and $\mathcal{G}$ respectively.
- Consequently, we proposed a unified indoor-outdoor localization solution that leverages transfer learning (TL) and U-MLP schemes to build a single DNN model as shown in Fig 2a and 2b, respectively.

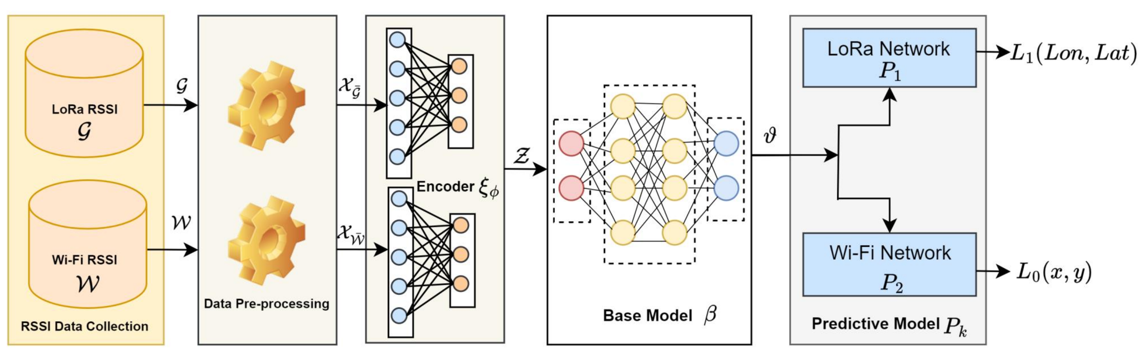

Figure 2a: Proposed Encoder-based system.

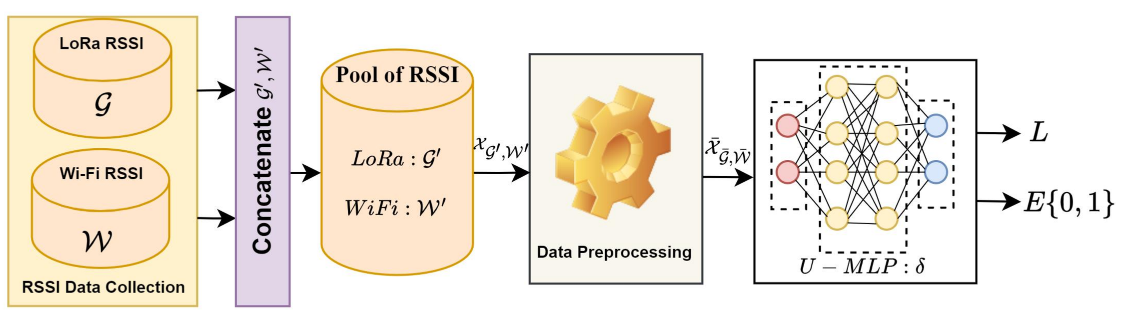

Figure 2b: Proposed U-MLP system.

Problem Formulation

- An artificial neural network-based (ANN) encoder $\xi_\phi : \mathcal{X} \longrightarrow \mathcal{Z}$ that aim to learn efficient representation of an input space $\mathcal{X} \in \mathbb{R}^{\overline{\mathcal{W}}} \cup \mathbb{R}^{\overline{\mathcal{G}}}$ and output latent space $\mathcal{Z} \in \mathbb{R}^n$. Hence, the encoder can be expressed as:

$$z = \xi_\phi(x). \tag{1}$$

- Encoder ξ_ϕ is implemented as an $n - layer$ ANN where the prediction for each hidden layer h is given by:

$$x_{h+1} = \sigma_h(W_h^T x_h + b_h), h = 0, 1, \cdots, n-2 \tag{2}$$

- TL leverages knowledge from a source environment S to enhance learning in a target environment T.
- We aim to find a function $f(\cdot)$ that minimizes the expected loss on the source environments. Hence, our formulated optimization problem is given by:

$$L(\theta^S) = \mathbb{E}_{(x_S, y_S)} \sim \mathcal{P}_S[\ell(f(x_S; \theta^S), y_S)], \tag{3}$$

- The source environment is initialized by $\theta_0^S = (\xi_0^S, \beta_0^S, P_{k0}^S)$
- After training θ^S model by minimizing the loss in Eq. (3), we end up with the optimal parameters given as:

$$\theta_*^S = argmaxL(\theta^S)$$

- The optimal model for the source environment is $\theta_*^S = (\xi_*^S, \beta_*^S, P_{k*}^S)$, also known as the pretrained model.
- By leveraging the pretrained parameters of the base model β_*^S as a starting point for training our model θ^T in the target environment. we initialized model θ^T by $\theta_0^T = (\xi_0^T, \beta_*^S, P_{k0}^T)$.
- Hence, we aim to get an approximation to the optimal parameters θ_*^T by iteratively running N steps of SGD using the following equation:

$$\theta_{i+1}^T = \theta_i^T - \alpha \nabla \mathrm{L}(\theta_i^T), i = 1, \ldots, N-1 \tag{4}$$

System Evaluation Metrics

- Indoor (Wi-Fi dataset): mean distant error (MDE) metric to calculate the average Euclidean distance error between the predicted location and the actual location.

$$MDE = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_i - \bar{x}_i)^2 + (y_i - \bar{y}_i)^2}, \tag{5}$$

- Outdoor (LoRa dataset): Haversine equation to measure the geodesic distance between two points on a curved surface.

$$d = 2Rarcsin\left(\sqrt{sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + cos\phi_1 cos\phi_2 sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right), \tag{6}$$

Result Analysis

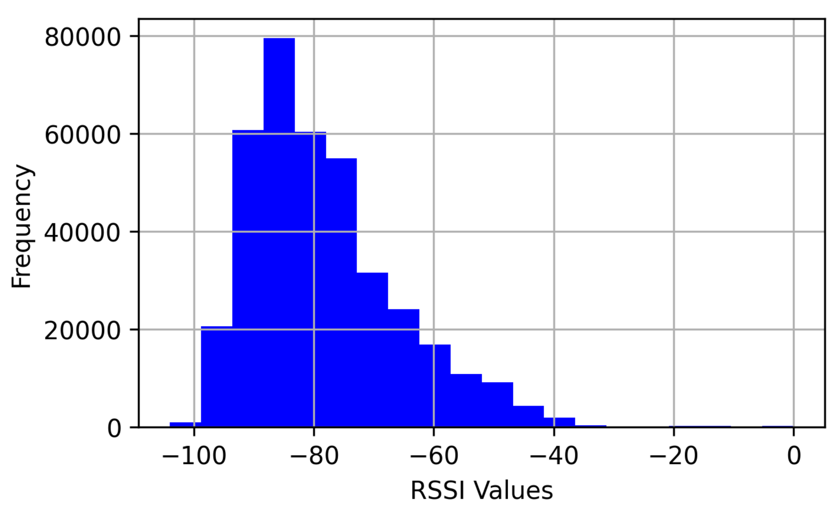

Figure 3a: RSSI values for indoor measurements *(dBm)*.

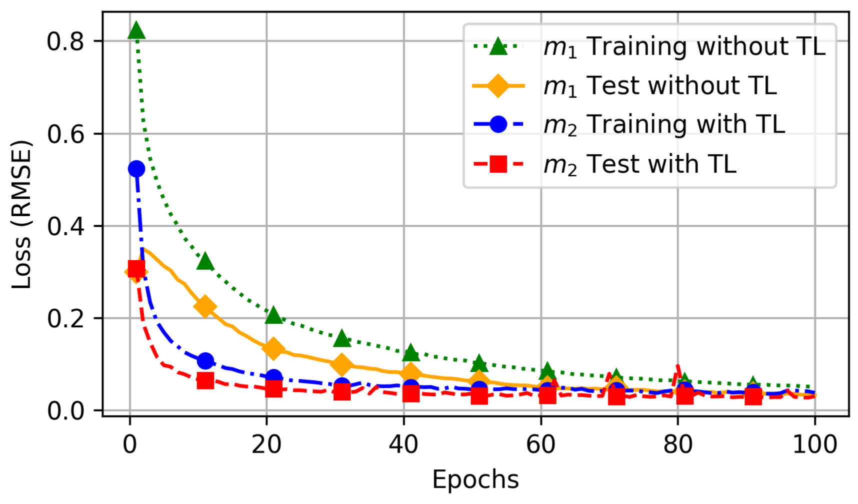

Figure 4a: Indoor Environment Training.

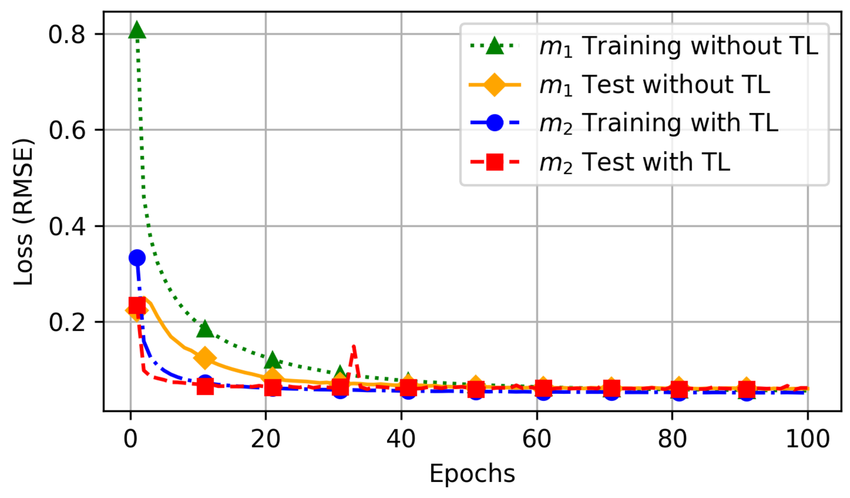

Figure 4b: Outdoor Environment Training.

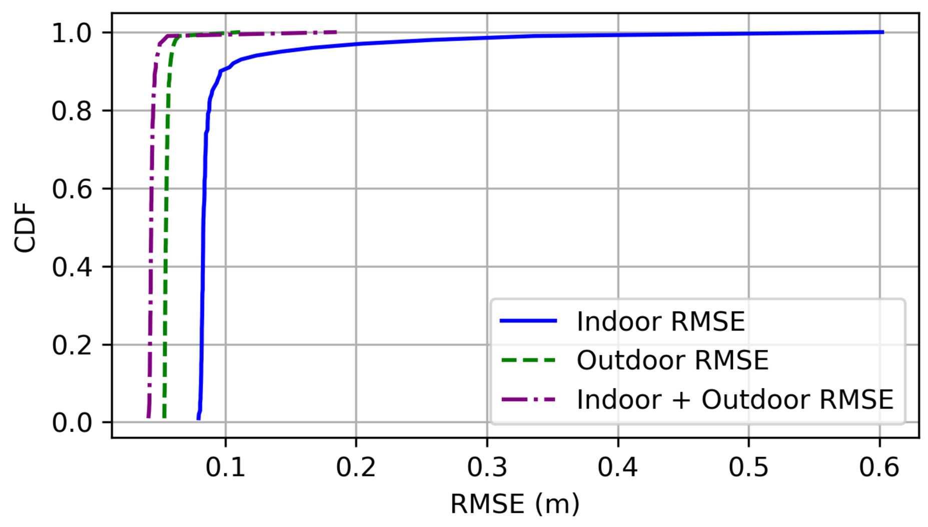

Figure 5: CDFs of RMSE for Indoor, Outdoor and Combined

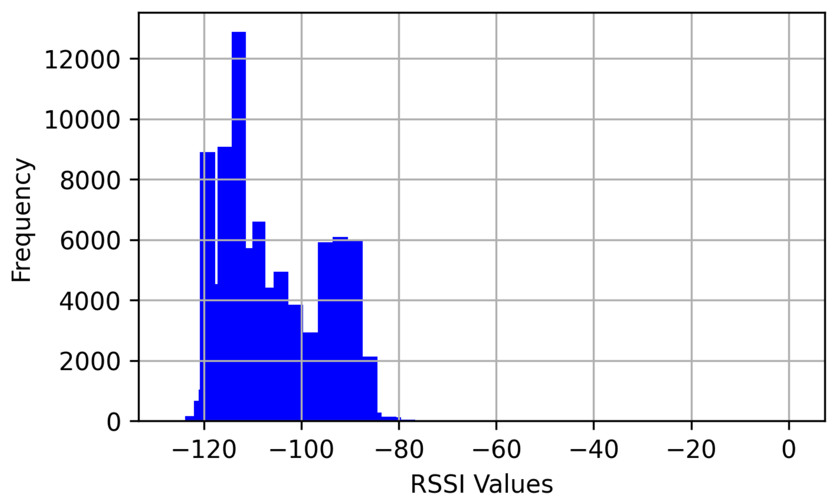

Figure 3b: RSSI values for outdoor measurements *(dBm)*.

Table I: Comparison of the positioning performance of our proposed models with state-of-the-art.

Indoor Environment		Outdoor Environment	
Models	**MDE (m)**	**Models**	**MDE (m)**
Baseline [11]	7.90	Baseline [10]	398.40
HADNN [13]	14.93	NN [12]	357
EA-CNN [14]	8.34	Ex. Trees [12]	379
Proposed encoder	**6.65**	Proposed encoder	361.21
Proposed U-MLP	9.61	**Proposed U-MLP**	**341.94**

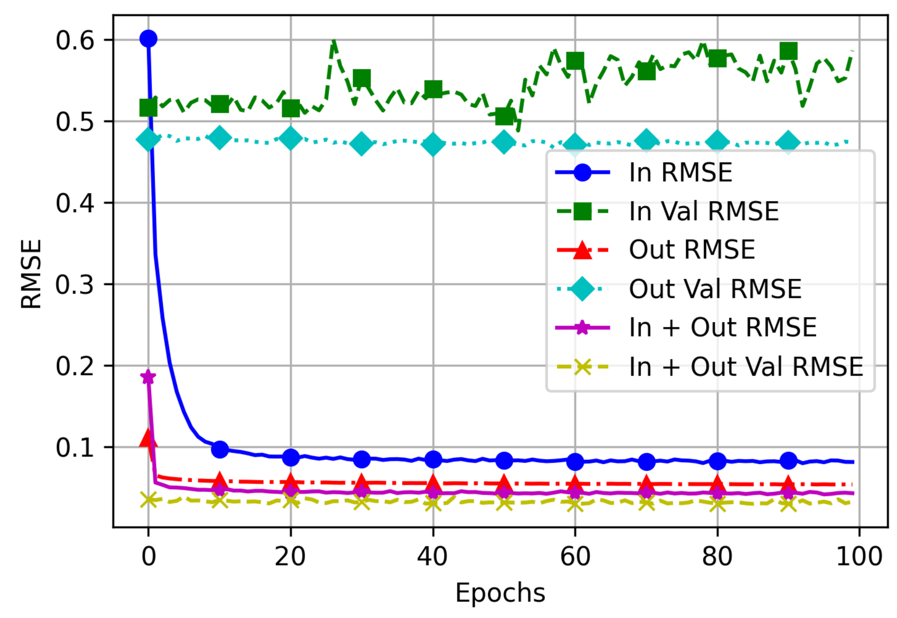

Figure 6: RMSE of U-MLP model on Indoor, Outdoor and Combined datasets.

Conclusion and Future work

In conclusion, we present an encoder-based TL and U-MLP model for accurate IoT localization using RSSI fingerprinting. The Encoder-TL framework demonstrated an improvement in baseline model performance of 17.18% (MDE: 6.65m) indoors and 9.79% (The MDE was 361.21 m outdoors, while the U-MLP model achieved an indoor MDE of 9.61 m and an outdoor MDE of 341.94 m. Future work will focus on exploring additional data sources from diverse environments and enhancing model security against potential threats.

References

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[3] A. Gadhgadhi, Y. Hachaïchi, and H. Zairi, "A Machine Learning based Indoor Localization," *4th International Conference on Advanced Systems and Emergent Technologies (IC-ASET)*, pp. 33-38, 2020.
[4] M. Safar Asaad and H.S. Maghdid, "A Comprehensive Review of Indoor/Outdoor Localization Solutions in IoT era: Research Challenges and Future Perspectives," *Computer Networks*, vol. 212, 2022.