International Journal of Engineering in Computer Science

E-ISSN: 2663-3590
P-ISSN: 2663-3582
Impact Factor (RJIF): 5.52
www.computersciencejournals.com/ijecs
IJECS 2026; 8(2): 10-15
Received: 06-02-2026
Accepted: 08-03-2026

P Pavani Sri Katyayini
Assistant Professor,
Department of Computer Science and Engineering, Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, Andhra Pradesh, India

Meghana Y
Department of Computer Science and Engineering, Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, Andhra Pradesh, India

P Kusuma Sri
Department of Computer Science and Engineering, Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, Andhra Pradesh, India

M Yedukondalu
Department of Computer Science and Engineering, Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, Andhra Pradesh, India

M Gayathri
Department of Computer Science and Engineering, Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, Andhra Pradesh, India

Corresponding Author:
P Pavani Sri Katyayini
Assistant Professor,
Department of Computer Science and Engineering, Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, Andhra Pradesh, India

Scalable deep similarity-based wi-fi fingerprinting for real-time indoor location identification and signal quality assessment

P Pavani Sri Katyayini, Meghana Y, P Kusuma Sri, M Yedukondalu and M Gayathri

DOI: https://www.doi.org/10.33545/26633582.2026.v8.i2a.271

Abstract
Indoor localization is a critical application in smart spaces where GPS is simply not reliable. Wi-Fi fingerprinting is the most popular technique for this purpose, as it utilizes the already present wireless infrastructure and does not require any additional hardware. However, traditional fingerprinting techniques usually fail in the presence of dynamic indoor environments and random signal patterns. To address these challenges, a scalable localization framework combining machine learning and deep learning is proposed. At its foundation is a deep similarity network that translates RSSI fingerprints into an embedding space where similar geometric locations are close by. After the fingerprints are embedded, a machine learning inference task is used to compare the current fingerprint with the precomputed reference embeddings to deduce the most probable location. However, localization is not the only problem that needs to be solved. The system also contains a real-time signal monitoring component. It observes RSSI variations and connectivity status during active Wi-Fi scanning. A real-time dashboard is then used to display system status, signal behavior, and localization updates as they occur. Experimental evaluations demonstrate that the system provides reliable localization predictions and scales the fingerprint database over time without requiring any additional training of the model.

Keywords: Indoor localization, wi-fi fingerprinting, rssi-based positioning, deep similarity learning, signal quality assessment

Introduction

The proliferation of smart space and location-based services has brought positioning within buildings into the spotlight. GPS works wonders outside, but inside, its effectiveness diminishes significantly due to the presence of walls, atten- uation of signal strength, and multipath effects. As such, humans have resorted to other techniques to accurately pin down locations within buildings. Among the techniques, Wi- Fi fingerprinting appears to be more promising as it makes use of the pre-existing infrastructure instead of requiring additional hardware to be installed. The typical setup of the fingerprinting technique requires the determination of the RSSI at certain locations to obtain the radio map of the environment. Once the device starts to move, the RSSI pattern of the device matches the fingerprints to obtain the location. The common techniques used are based on distances such as Euclidean distance, cosine similarity, and k-NN. Although these techniques are effective, they are often disrupted by the changing signal strength due to the dynamic nature of the surrounding environment. However, recent advances in machine learning and deep learning are now providing new avenues for indoor localization. Deep learning models have the capability to extract complex patterns from high-dimensional signal data and represent RSSI fingerprints in a more interpretable manner. Many research papers have uti- lized neural networks to understand the relationship between signal measurements and location in space. However, many of these methods have formulated the localization problem as a closed-set classification problem, where each reference Location is considered a separate class. This can be a problem when it comes to scalability, as it may be necessary to retrain the model for new reference locations or when the environment changes

To address this problem, similarity-based learning algorithms have been introduced. These methods aim to learn the relationships between fingerprints rather than learning the direct relationship between fingerprints and locations. In this approach, fingerprints of locations close to each other are drawn closer together in the embedding space, while those of locations that are far apart are pushed further apart. This embedding maintains the spatial consistency and improves robustness for indoor localization in environments where the signal patterns change over time.

Motivated by these observations, a scalable indoor localization framework that combines machine learning and deep learning techniques is developed in this study. The proposed approach employs a deep similarity network to transform Wi- Fi RSSI fingerprints into a compact embedding space that captures spatial relationships between signal measurements. Machine learning-based inference is then used to compare observed fingerprints with stored reference embeddings to estimate the most probable indoor location. In addition to localization, the system integrates a real-time signal monitor- ing component that analyzes RSSI variations, signal strength behavior, and connectivity trends during continuous Wi-Fi scanning. A visualization dashboard is also implemented to display system status, signal analytics, and localization up- dates, enabling effective monitoring of indoor wireless envi- ronments.

The contributions of our project can be summarized as follows. First, a scalable Wi-Fi fingerprinting framework inte- grating machine learning and deep similarity learning is devel- oped for indoor localization. Second, the proposed similarity- based embedding mechanism preserves spatial relationships among RSSI fingerprints and enables incremental updates of reference points without retraining the model. Third, a real- time signal monitoring and visualization module is introduced to analyze RSSI behavior and connectivity conditions during system operation.An end-to-end implementation is used to illustrate the applicability of the proposed framework to the task of indoor localization and signal analysis in a dynamic environment.

Section II discusses the related work in the field of Wi- Fi fingerprinting and learning-based localization techniques. Section III explains the proposed methodology and the overall architecture of the system. Section IV explains the imple- mentation and experiment sections. Section V discusses the experiment and evaluation of the proposed system. Section VI concludes the overall paper and discusses possible future directions.

Related work

Bahl and Padmanabhan [1] proposed the RADAR system, one of the most popular Wi-Fi-based fingerprinting techniques. They proved that the received signal strength indicator (RSSI) Values, collected from several access points, can be used to estimate the position of users in a building. Youssef and Agrawala [2] proposed another popular method called Horus WLAN localization. They used the probabilistic distribution of signal strength values to improve the accuracy of localization. Liu *et al* [3]. proposed a survey of wireless indoor localization techniques. They identified some drawbacks in the accuracy of the RSSI-based localization technique, including the instability of wireless signals in complex areas.

To improve the accuracy of localization, several researchers have used machine learning techniques. He and Chan [4] pro- posed learning-based fingerprinting techniques. They proved that machine learning techniques can improve the accuracy of localization because they can better understand the relationship between signal values and locations. With the increasing computational capabilities of devices, deep learning techniques have been used in wireless fingerprinting techniques.

Zhang *et al* [5]. developed a deep learning-based indoor positioning system that utilizes neural networks to learn com- plex patterns from RSSI measurements. Similarly, Wang *et al* [6]. proposed a deep learning framework that aims to enhance the robustness of Wi-Fi fingerprinting in varying environmental conditions. These studies have clearly proved that deep learning can be used to enhance the representation of features in signal-based localization.

However, in recent deep learning-based localization systems, it has been observed that they have used classification as an approach to perform localization. In this approach, each reference point is considered as a separate class. This might affect the scalability of the localization approach, as in the case of changes to the reference points, the entire deep learning approach has to be retrained. In recent years, similarity-based learning has been proposed as an alternative approach.

Hadsell *et al* [7]. proposed contrastive learning approaches that can be used to learn invariant representations. This allows the neural networks to learn the difference between similar and dissimilar samples. Chopra *et al* [8]. proposed similarity metric learning approaches using neural networks. This has been extended to the development of the Siamese network. Deep metric learning has also been used to perform recognition tasks.

Schroff *et al* [9]. proposed the FaceNet approach, which can be used to learn a compact embedding.Wen *et al* [10]. pro- posed a discriminative feature learning method that increases the separability of features learned in deep networks. The aforementioned studies have proven the efficiency of using embedded learning for complex pattern recognition tasks.

Lee and Seo [11] have developed a scalable framework for Wi- Fi fingerprinting localization using deep similarity networks. The study used deep learning for pattern recognition, trans- forming the problem into a similarity estimation problem in- stead of a classification problem, enabling the addition of new reference points without the need for retraining the network. Kaya and Bilge [12] have also proven the efficiency of using deep metric learning for learning compact and discriminative embeddings for high-dimensional datasets. Other studies have

Focused on developing hybrid solutions for improving the efficiency of the localization process.

Seong *et al* [13]. have developed a high-speed localization framework using a hybrid approach that combines Wi-Fi and ultra-wideband technologies for improving the reliability of the localization process. Recently, Pandey *et al* [14]. have developed a Siamese network-based localization method for IoT environments, enhancing the robustness of the localization process against signal changes.Chen and Zhang [15] also investigated the use of deep metric learning for Wi-Fi fin- gerprinting and reported improved localization robustness in noisy wireless environments.

Even though these studies have made a substantial contribution to the development of Wi-Fi fingerprinting systems, many of the solutions currently in use prioritize increasing localization accuracy over system-level features like real-time signal mon- itoring and visualization. Moreover, only a small number of methods integrate continuous signal behavior analysis during system operation with scalable similarity-based localization. A framework that combines deep similarity learning with ma- chine learning-based inference and real-time signal monitoring is created in order to overcome these difficulties. Through an interactive visualization interface, the suggested system not only estimates indoor locations but also continuously analyzes RSSI behavior and connectivity conditions.

Methodology

The proposed system adopts a modular and similarity-driven approach for real-time indoor localization and signal quality evaluation using Wi-Fi fingerprinting. The entire process in- volves Wi-Fi data acquisition, preprocessing, deep similarity embedding, reference database generation, similarity-driven inference, signal quality assessment, tracking, and visualiza- tion, as shown in Fig. I and listed in Table I.

Table I: Description of methodology phases

Phase Name	Description
Wi-Fi Data Acquisition	Collection of RSSI and access point information through repeated Wi-Fi scans
Feature Processing & Embedding	RSSI normalizationand transformation into similarity embeddings using a Siamese network
Reference Database	Storage of reference embed-dings for scalable localiza- tion
Signal Quality Assessment	Evaluation of connectivity quality alongside localiza- tion

Table I lists the major steps involved in the proposed Wi-Fi fingerprinting system, which explains the entire process from RSSI data acquisition to similarity-driven localization.

Wi-Fi Data Acquisition

The initial stage of this system involves data acquisition. This phase entails the measurement of Wi-Fi signals at designated reference points within the indoor environment. To gather data on the attributes of proximate access points, multiple Wi-Fi scans are performed at each reference location. Each scan records information, including the Basic Service Set Identifier (BSSID), RSSI, channel number, and operating frequency of the detected access points. These individual measurements are referred to as a collective measurement. These collective measurements define a Wi-Fi fingerprint.To understand how environmental factors like user movement and signal interference affect Received Signal Strength Indicator (RSSI) values, multiple fingerprints are collected at each reference point.

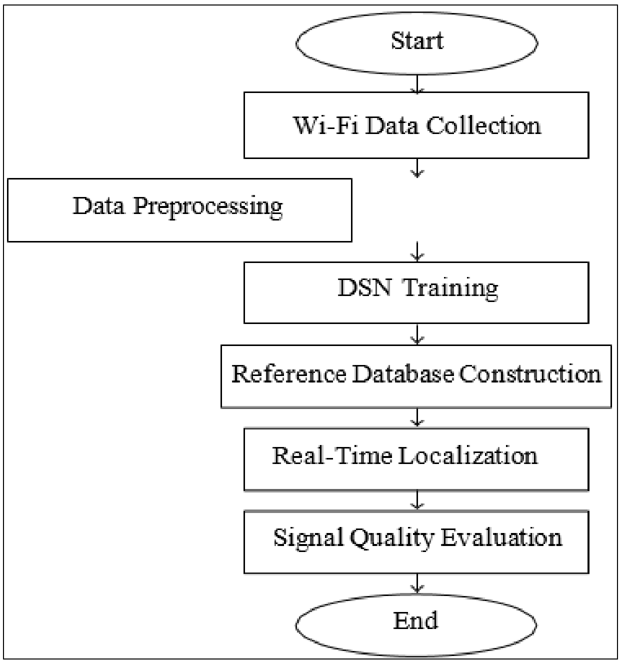

Fig 1: Overall workflow of the proposed Wi-Fi fingerprinting and localization framework

The overall workflow of the proposed indoor localization framework is presented in Fig. 1. The Wi-Fi RSSI mea- surements are collected by performing multiple scans. The collected measurements are then preprocessed to form finger-print vectors. The fingerprint vectors are then fed into a deep similarity network, which transforms the fingerprint vectors into embedding form. The embedding vectors are stored in a reference database. The location of the device is calculated by comparing the fingerprint vectors with the embedding vectors. The variations in the strength of the signals are monitored.

Fingerprint preprocessing

Before training the model, the collected Wi-Fi fingerprints undergo preprocessing. Because the number of detected access points varies during scans, preprocessing is necessary to convert the acquired signals into fixed-length feature vectors. Initially, RSSI values are normalized to reduce fluctuations in signal strength. Zero padding is then applied to handle missing access point readings. Additional statistics about the extra signal, such as the average RSSI and the strongest signal seen, can be isolated to better understand the signal environment.

Deep similarity embedding

A deep similarity network is employed to capture the relationship between Wi-Fi fingerprints. This network learns an embedding to transform fingerprint vectors into a lowerdimensional space where similar fingerprints are close to each other. The embedding transformation is represented by

F: R^D→R^H (1)

$$L = \frac{1}{2N}\sum_{i=1}^{N}[y_i d_i^2 + (1 - y_i)\max(m - d_i, 0)^2] \quad (2)$$

Where N is the batch size, $y_i \in \{0, 1\}$ indicates whether the fingerprint pair belongs to the same location,d_i represents the distance between embeddings, and m is the margin parameter. The Euclidean distance is computed as

$$d_i = \left\| f(\mathbf{x}_i) - f(\mathbf{x}_j) \right\|_2 \quad (3)$$

This objective promotes the clustering of fingerprint embeddings within the same location to be closer together and the clustering of fingerprint embeddings from different locations to be further apart.

Reference database construction

Once the similarity network has been trained, the embeddings of fingerprints taken at each reference location are maintained within a reference database. For each location k, several fingerprint embeddings are combined to produce a reference embedding

$$\mathbf{r}_k = \frac{1}{n_k}\sum_{j=1}^{n_k} f\,(\mathbf{x}_{k,j}), \quad (4)$$

$$\mathrm{sim}(\mathbf{z}_{test}, \mathbf{r}_k) = \frac{\mathbf{z}_{test} \cdot \mathbf{r}_k}{\|\mathbf{z}_{test}\|\,\|\mathbf{r}_k\|}. \quad (5)$$

where "n" _"k" is the number of fingerprints collected at reference point "k" and "r" _"k" denotes the stored reference embedding. This database is the basis for the localization system and enables new reference fingerprints to be added without the need to retrain the model.

Similarity-based localization

In real-time localization, a new Wi-Fi scan is conducted to determine the current fingerprint of the device. The fingerprint is preprocessed and then fed into the trained similarity network to produce its embedding representation.

The embedding is compared to the reference embeddings in the database using cosine similarity

The reference location with the highest similarity score

Is chosen as the predicted location.

Signal monitoring and visualization

Apart from the localization process, the system also monitors the signal behavior during its operation. The RSSI values derived from the consecutive scans are analyzed to monitor the signal variations and connectivity status. The signal measurements are presented through a monitoring dashboard that shows the system status, signal strength trends, and localization updates in real time. The monitoring dashboard allows the user to analyze the signal trends and understand the connectivity status in the indoor environment.

Implementation

Development environment

The proposed indoor localization system was developed using Python because of its rich set of machine learning and deep learning libraries. The deep similarity model was built using TensorFlow and Keras, which are efficient tools for designing and training neural network architectures. Data processing and numerical computations were carried out using the NumPy and Pandas libraries. For visualizing and analyzing the signal behavior, libraries such as Matplotlib and Plotly were used to plot graphical representations of RSSI changes and signal monitoring results.

System architecture and backend

The backend of the system was built using the Flask web framework, which is an efficient tool for developing lightweight web applications. The backend system handles Wi-Fi scan data, similarity-based localization inference, and real- time localization result delivery via REST APIs. A SQLite database was used to store Wi-Fi fingerprints, reference em- beddings, and scan results. The database design allows for efficient retrieval of reference fingerprints during similarity- based localization

Real-time localization interface

To facilitate system monitoring and visualization, a web-based interface was designed to show real-time results of localization and signal activity. The interface offers system status, scan number, signal strength trends, and localization updates. The system is able to scan Wi-Fi continuously to analyze RSSI changes over time and show signal patterns in the indoor environment.

Results and discussion

Experimental configuration

A real indoor environment with several rooms and Wi-Fi access points was used to test the suggested indoor localization system. In order to record Wi-Fi fingerprints through con-tinuous Wi-Fi scanning by a mobile device, the environment needed particular reference points. Researchers were able to examine how environmental factors, such as user movement, access point changes, and signal interference, affected signal strength by conducting multiple scans at each reference point. RSSI values from the nearby access points were used to create a fingerprint for each scan. These fingerprints helped create the reference database that the similarity-based localization framework required. In order to identify the most likely location within the building, the trained similarity network analyzed fresh Wi-Fi scans during the testing phase.Apart from localization, the system continuously tracked signal behavior over several scans to examine changes in signal strength and connectivity in the interior space.

RSSI monitoring in real time

Continuous Wi-Fi scans were carried out while tracking the change in RSSI values over time in order to comprehend the behavior of Wi-Fi signals during system operation. The monitoring procedure recorded the strongest signal found during each scan as well as the average signal strength across all identified access points.

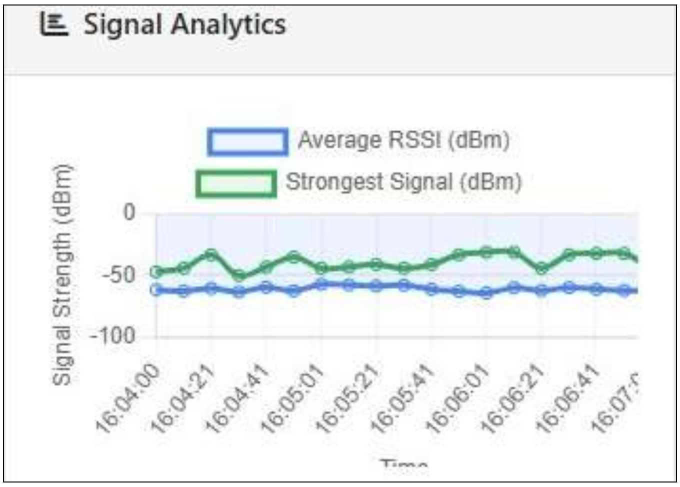

Fig 2: The strongest signal strength and average rssi fluctuate over time during successive wi-fi scans.

The findings show that environmental factors like user movement and signal reflections cause RSSI values to change between consecutive scans. Nonetheless, within a constrained range, the overall signal trend stays comparatively stable. Keeping an eye on these signal fluctuations offers help- ful information about how wireless connectivity behaves in- doors. The reliability of Wi-Fi fingerprints used for localization can also be assessed by tracking signal changes over time.

Localization stability

By conducting multiple scans at the same reference location and examining the anticipated outcomes produced by the similarity-based inference mechanism, the stability of the localization system was assessed. Each scan's fingerprint was converted into an embedding representation, which was then compared to the database's reference embeddings. When the device stayed in the same place, the similarity-based method reliably found reference points with high similarity scores. The system was able to maintain stable localization predictions despite slight variations in RSSI measurements due to the embedding-based representation. This behavior shows how similarity learning can reduce the impact of signal noise and increase localization reliability by capturing significant relationships between Wi-Fi fingerprints.

Real-time processing and system performance

The suggested framework was created to facilitate signal monitoring and real-time localization. In order to create an embedding representation of the observed fingerprint, the deep similarity network processed every Wi-Fi scan during operation. Using similarity matching, this embedding was then contrasted with reference embeddings kept in the database. The system produced location predictions with little delay because the similarity comparison only required a small amount of computation. Practical indoor positioning appli- cations depend on near real-time localization updates, which are made possible by this. The system continuously updated the monitoring dashboard with new signal measurements and anticipated locations in addition to localization. Users were given information about system status, scan counts, signal strength trends, and connectivity conditions through this real- time visualization.

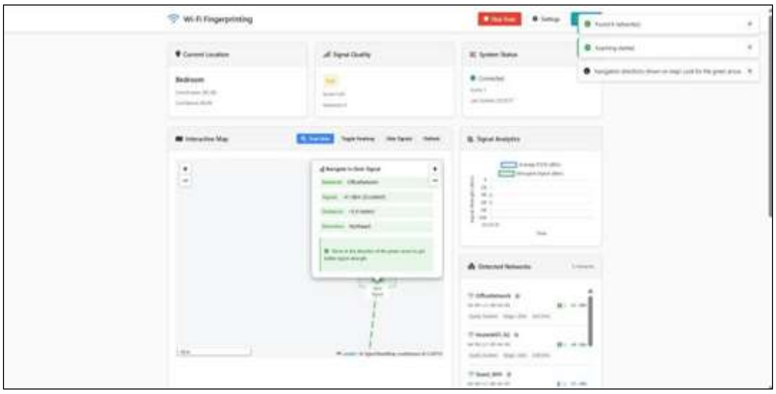

Fig. 3: Real-time system dashboard displaying wi-fi fingerprint localization results, detected networks, rssi monitoring, and navigation toward the strongest signal source.

The screenshot in Fig. 3 shows the real-time monitoring dashboard of the proposed Wi-Fi fingerprinting system. The dashboard displays three elements which include the detected Wi-Fi network and the signal quality and the predicted loca-tion. The system provides users with navigation directions to reach the access point that shows the highest RSSI measure-ment. The RSSI measurement graph shows the variation in RSSI measurement from one scan to another.

Discussion

The experimental observations suggest that the Wi-Fi sig- nal strength values tend to vary in natural circumstances because of environmental dynamics like signal reflection, user movement, and other device interference. However, the similarity-based embedding approach helps the system to sustain its stability in providing accurate predictions. The proposed approach is different from other classification-based approaches in the sense that it relies on similarity compar-ison in an embedding space. This helps in achieving better scalability, where new reference fingerprints can be added to the database without retraining the model. The addition of signal monitoring attributes also helps in providing better understanding of the behavior of the wireless network in the indoor environment, where the trends in RSSI and variations in signal strength can be used to perform connectivity analysis. The above attributes suggest the potential of applying machine learning, deep learning, and signal monitoring techniques to design practical systems for indoor localization.

Conclusion and future work

Reliable localization of objects through these methods is still a problem due to changing conditions in the wireless signals. The Wi-Fi fingerprinting framework for deep simi-larity learning and machine learning inference was proposed for overcoming these challenges in object localization. The experimental results show that the proposed system ensures reliable performance in object localization even in changing RSSI values. Apart from object localization, the proposed framework is useful for understanding the changes in the wireless connectivity environment through the visualization of changes in RSSI and network trends of the signals.

The proposed framework for object localization using Wi-Fi fingerprinting and similarity learning can be further extended in the future by integrating various object localization tech- niques using Wi-Fi fingerprinting and other wireless commu-nication technologies like Bluetooth Low Energy Technology and Ultra Wideband Wireless Communication Technology for object localization. The proposed framework can be further extended to achieve accurate visualization of network names and wireless signal sources by integrating Wi-Fi network APIs to achieve accurate navigation of objects towards the strongest access points in the network.

References

1. Bahl P, Padmanabhan VN. RADAR: An in-building RF-based user location and tracking system. In: Proc IEEE INFOCOM; 2000.
2. Youssef M, Agrawala A. The Horus WLAN location determination system. In: Proc MobiSys; 2005.
3. Liu H, Darabi H, Banerjee P, Liu J. Survey of wireless indoor positioning techniques and systems. IEEE Trans Syst Man Cybern. 2007.
4. He S, Chan SHG. Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons. IEEE Commun Surv Tutor. 2016.
5. Zhang W, *et al*. A deep learning based indoor positioning system using Wi-Fi signals. In: Proc IEEE ICC; 2016.
6. Wang S, Xie J, Zhang X. Deep learning-based robust Wi-Fi fingerprinting for indoor positioning. IEEE Access. 2020.
7. Hadsell R, Chopra S, LeCun Y. Dimensionality reduction by learning an invariant mapping. In: Proc IEEE CVPR; 2006.
8. Chopra S, Hadsell R, LeCun Y. learning a similarity metric discriminatively. In: Proc IEEE CVPR; 2005.
9. Schroff F, Kalenichenko D, Philbin J. FaceNet: A unified embedding for face recognition and clustering. In: Proc IEEE CVPR; 2015.
10. Wen Y, *et al*. A discriminative feature learning approach for deep face recognition. In: Proc ECCV; 2016.
11. Lee SH, Seo DH. Scalable Wi-Fi fingerprinting localization by deep similarity network. IEEE Internet Things J. 2023.
12. Kaya M, Bilge HS. Deep metric learning: A survey. Symmetry. 2019.
13. Seong JH, *et al*. High-speed positioning and automatic updating technique using Wi-Fi and UWB. Wirel Pers Commun. 2017.
14. Pandey A, *et al*. RSS-based Siamese embedding location estimator for dynamic IoT environments. IEEE Internet Things J. 2022.
15. Chen P, Zhang S. DeepMetricFi: Improving Wi-Fi fingerprinting localization by deep metric learning. IEEE Internet Things J. 2024.