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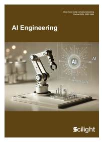

Review

Wireless Localization Using Deep Learning: A Survey

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How To Cite: Xia, H.; Andrews, M.; Conti, A.; et al. Wireless Localization Using Deep Learning: A Survey. *AI Engineering* **2026**, *2*(1), 1. https://doi.org/10.53941/aieng.2026.100001

Received: 7 August 2025
Revised: 1 December 2025
Accepted: 4 January 2026
Published: 20 January 2026

Abstract: The demand of localization services continuously rises with the advancing and developing of mobile and Internet of Things (IoT) devices in the last decade. Localization based on various wireless standards have been extensively studied to provide services in different applications. With the emergence of deep learning (DL) algorithms, many different DL models or architectures are utilized in localization tasks to increase the accuracy and robustness over conventional localization methods. However, there is a lack of survey paper that focuses on how different DL-related methodologies are adopted in corresponding localization scenarios. In this paper, we aim at presenting a comprehensive and up-to-date review of DL-based localization methods from the respects of those common wireless standards such as Wi-Fi, cellular, ultra-wideband (UWB) and Bluetooth low energy (BLE). We further highlight those factors that build up end-to-end DL-based methods including the datasets, preprocessing methods, and DL algorithms. We also discuss how DL can potentially address the challenges in terms of localization precision, latency, and data generation.

Keywords: localization; deep learning; Wi-Fi; cellular system; IoT; UWB; BLE

1. Introduction

Wireless localization is becoming a very important technology providing various services in an indoor or outdoor environment. With the increasing deployment Internet of Things (IoT) services and devices, tracking or monitoring the activities of individuals or electronic devices is the foundation of applications such as navigation, health care, and trajectory planing [1–3]. A typical wireless localization system consists of two parts: an anchor and a target. Usually, the anchor device will keep broadcasting radio waves to the nearby targets. The target nodes or devices will monitor these localization inquiries over the wireless communications channel and then send signals back to the anchor to report their location data. Finally, the anchor will use the received data to estimate the location of the target. Such localization process is depicted in Figure 1, where a deep learning (DL) algorithm is applied to map the signal data to spatial coordinate of the target. Also, in some cases where the target nodes do not equipped with any active wireless transmitter, the anchor can also analyze the target location by capturing the signals, e.g., Wi-Fi signals, reflected from the target [4,5].

In fact, many of the common wireless technologies, including Wi-Fi, cellular, Bluetooth low energy (BLE) and ultrawide band (UWB) have been studied and developed to provide localization services. Since all these technologies have their dedicated coverage or unique signal properties, each of them is adopted in different deployment scenarios for the corresponding localization applications. For instance, Wi-Fi is mostly used in indoor environments, which makes it the most natural option to support indoor localization service. Also the widely deployed Wi-Fi infrastructure and devices save the cost on expanding the services. Similarly, Long-Term Evolution (LTE) or 5G signal suit more for outdoor localization tasks because they can provide better coverage and transmission quality in urban or wide open area [6–8]. On the other hand, the localization performance also suffers from the characteristics of the wireless technologies. For example, although the UWB-based system can generally achieve centimeter level localization accuracy, its performance will be greatly affected in non-line of sight (NLOS) environments due to its weak signal penetration. A similar problem also exists in BLE-based localization systems, because the weak signal penetration affects the coverage of BLE devices. In general, the choice of a wireless standard needs to take these properties into account to fit the requirement of a specific application. Usually, the main concern of the localization service, such as precision, coverage, latency, or cost, can be different depending on the application scenario.

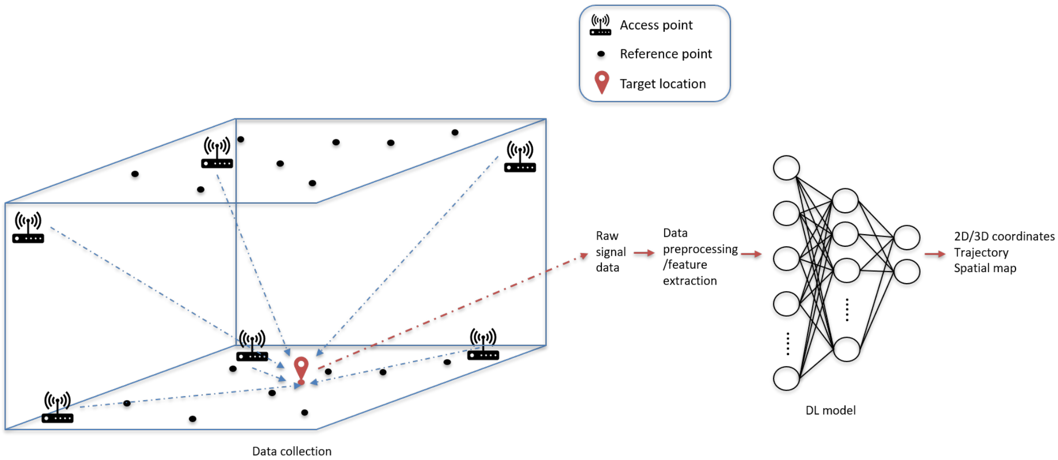

Figure 1. General flow of a DL-based localization system.

Therefore, how to compensating the shortcomings of different wireless technologies or further enhancing the localization performance are still challenging tasks. Recent studies and research focus on developing advanced localization methods to achieve higher-resolution localization accuracy or increase the robustness in different environments. Localization methods, in general, can be categorized into range-based methods and range-free methods. The former one requires that multiple anchors in the space need to monitor the signals transmitted back from the target and each of the anchors estimates their distance to the target accordingly. Then a multi-lateration problem can be formed using the distance information to estimate the location of the target, which usually makes the problem a non-linear one. This type of method, even though is able to achieve solid localization accuracy, does not fit well into the application with NLOS environments, because any obstruction between the anchors and the target can deteriorate the distance estimation [3,9,10]. Localization accuracy is highly dependent on the channel or environment modeling, which can be challenging and inaccurate in practical scenarios due to NLOS effect, fading, etc. [11]. The range-free methods, however, have looser constraints on the complexity of the environment [12]. The signal exchange between anchors and reference points in the space builds a profile, which is also called fingerprint, for each reference point [13]. Then when coming to the localization steps, the fingerprint of the target will be compared with the fingerprints of all the reference points to find the best match. However, both types of the methods requires the predefined environment information or geometrical model of the space where the localization is performed. Practically, the environment information can be very limited or even unknown [14]. The methods may not have enough generality for different environments, or be robust enough to any fluctuations of signals [5].

One of the main reasons that DL algorithms start to be adopted in localization problems is to capture the complexity or variation in the environment or wireless channel in a learning manner [5]. Through the data-driven process, one will be able to train a DL model using the distance data or fingerprint collected from the reference points all over the space in order to get a more accurate representation of the environment, and thus provide more accurate location estimation even in complex environments. Also, with the learning mechanism, the DL model can be updated with real-time collected data so that it will be more robust to any changes in the environment [15]. Moreover, the mapping between the received signal data to the location information is nonlinear, while DL algorithms have been validated to be an effective approximator to such kind of relationship [16].

While DL algorithms are being studied and utilized in wireless localization problems, related works have also been summarized by several reviews and survey papers from various perspectives. Ref. [17] mainly categorizes ML and DL related works according to the corresponding types of localization technologies used, such as optic-based, radio frequency (RF)-based and acoustic-based localization, etc. Refs. [18–20] focus more on RF-based localization methods that uses ML algorithms or some fundamental DL architectures like CNN and RNN. Some reviews aim at one or some certain types of localization technologies only. The authors in [21] summarize DL-based indoor localization methods in Wi-Fi environment only. The ones of [8] concentrate on the works in 5G and future 6G localization deployment scenarios. Moreover, in [22], the authors dedicated significant efforts in how ML algorithms improve localization performance in various scenarios like NLOS and minimize signal fluctuation. Alhomayani and Mahoor emphasis on fingerprint-based localization methods, and summarizes the related studies based on the types of DL algorithms implemented in [23]. They also include a summary of available fingerprint datasets in their review. Ye et al. categorize the related works into device-oriented and device-free localization [24]. Besides DL related surveys, there are also reviews and report like [6,13,25], focusing more on the theoretical modeling and analysis of localization problems, which are also considered to be informative and insightful to the this research area. The major focuses and novelties of our work are further highlighted Table 1 comparing with other state-of-art survey paper in the related fields.

Table 1. Existing survey papers in the literature.

Source Article	Coverage									
	DL	**Wi-Fi**	**Cellular**	**Other Wireless Technology**	**Data Preprocessing**	**Dataset**	**DL Algorithm**	**Simulator**	**Indoor**	**Outdoor**
Burghal 2020 [18]	Y	Y	Y	Y		Y			Y	Y
Feng 2022 [21]	Y	Y					Y		Y	
Nessa 2020 [22]	Y	Y	Y		Y				Y	
Hoffmann 2019 [13]			Y						Y	Y
Nikonowicz 2022 [6]			Y						Y	
Roy 2021 [19]	Y	Y		Y		Y			Y	
Alhomayani 2022 [23]	Y	Y	Y	Y		Y	Y		Y	
Mogyorosi 2022 [8]	Y	Y	Y	Y					Y	
Kordi 2024 [20]	Y	Y	Y	Y					Y	
Ye 2020 [24]	Y	Y							Y	Y
Zafari 2019 [25]		Y	Y	Y					Y	
Sonny 2024 [17]	Y	Y	Y	Y		Y			Y	
Our work	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

On the other hand, the existing survey papers do not summarize how to design and integrate the components of a DL model in order to fit the needs of various localization application scenarios. In addition, as DL algorithms and models are constantly and rapidly evolving, an up-to-date survey which takes those most advancing DL methods, such as generative AI (Gen-AI), is crucial for future research in wireless localization. Therefore, in this paper, we study and review the most recent research works that investigating the DL-based wireless localization methods to provide some systematic reviews and insights about related studies. We focus on how DL algorithms are being utilized under different wireless technologies. We also address three main components that contributes to the studies of DL-based localization methods, which are available datasets, data-preprocessing methods, and available simulators for wireless propagation. Moreover, we further discuss through categorizing the DL-related wireless localization works from these perspectives, we aim at providing the readers a comprehensive reference or guidance on how to choose/design the elements of a DL-based localization system under different circumstances. The key contributions are listed as follows.

1. We present a detailed and up-to-date survey of various DL-based wireless localization research works proposed from 2016 to 2024. We focus on those most recent studies from 2019 to 2024, which adopt the advancing DL algorithms.
2. This survey discusses the common issues and challenges existing in the localization with different wireless technologies, including Wi-Fi, cellular, UWB, and BLE, and provides a detailed summary about how DL models or algorithms address those problems.
3. We categorize and analyze the related studies by their design and implement choices of a DL-based localization system, including the datasets, data preprocessing method, DL algorithms, and wireless environment simulator. We are dedicated to present a comprehensive reference about how different methodologies are adopted in different scenarios or to address different issues, in order to support the design of the components in a DL system in future studies.
4. We further discuss the challenges of achieving sub-meter level accuracy and the latency problem in real-time deployment. We present some existing methods and also some potentially useful ones that can approach these issues by cooperating DL related algorithms.
5. We also discuss how some of the most advancing DL models such as Gen-AI can be utilized to improve the localization performance or improving the system efficiency.

The rest of the paper is organized as shown in Figure 2. In Section 2, we will present the localization datasets which are available for use, the common data preprocessing methods for various data, and the simulators available for researchers to emulate the environments and wireless channels. Sections 3–5 introduce the recent DL-based localization methods under different wireless systems. Sections 3 and 4 focus on Wi-Fi and cellular system-based localization, and Section 5 illustrate the localization under other common wireless systems including UWB and BLE. Section 6 provides some related discussions. Section 7 concludes the paper.

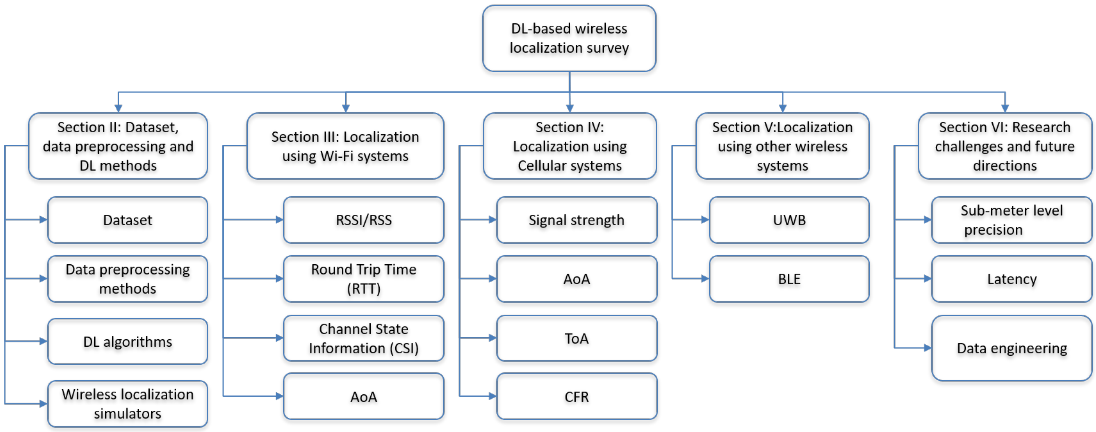

Figure 2. The structure of this paper.

2. Dataset, Data Preprocessing, and DL Methods

DL algorithms has become an effective solution in many applications thanks to its power in obtaining key features from a large dataset. In order to build an effective DL-based system, both the data and the DL algorithms are crucial. It is necessary to have a clean and accurate dataset to support the training of the learning model. At the same time, the choice of DL algorithms also needs to match the dedicated localization task, including the data format or those specific constrains of the corresponding applications. Therefore, in this section, we aim to summarize and categorize the recent wireless localization research works in the following two main perspectives: the data and the DL algorithms. Firstly, we tabulate those datasets that have open access to support the localization studies. We also highlight some of the commonly used data preprocessing methods for various data or applications. We believe that the data preprocessing in a crucial step that leads to the accomplishment of a DL-based localization task, due to the fact that most of the collected wireless data contain noisy or even jamming information which stops the DL algorithms from capturing the characteristics of the wireless signals, which can easily deteriorate the localization performance. As for the algorithms perspective, we summarize the recent works according to the types of DL model/method applied in the research. We also highlight some of the features such as the input data format in this section, to give the readers a sense of how the DL algorithms and preprocessing methods are chosen corresponding to the wireless data in different wireless environments. We believe that this summary can help to design the DL-based localization model in various scenarios.

2.1. Dataset

A high-quality dataset is usually considered to be the foundation of a successful DL-based system. In general, training a DL model requires that the size of the training dataset is large enough, and the data itself cannot be polluted with noise or other interferencing information. The later one is especially crucial in wireless communications tasks, due to the fact that wireless signal transmission can suffers from radiation, signals or noise from other resources, and obstacles in the space, etc. These are also some of the reasons why the current localization tasks are challenging, as any models or algorithms need to deal with these inherent problems of the data in order to achieve better accuracy on estimating the location. From the implementation point of view, a standardized and public available dataset can help to compare the performance of different models or algorithms [4]. In addition, the environments in which the dataset is measured or simulated should also contain a certain level of complexity and variety in order to further justify the performance and generality of the implemented DL-based methods. For example, NLOS environment has been considered to be one of the most challenging case especially in the indoor localization tasks as it is a type of scenario expected in many real-world applications. How to address the mobile targets/agents is also a focus of recent studies for some localization tasks such as trajectory monitoring or prediction. Therefore, in Table 2, we summarize those datasets which are (1) public available; (2) collected or generated in different environments, especially under different wireless technologies; and (3) commonly used in other related research works. We also include some of the newly published datasets to show more possibility of the data to be used in current or future localization applications.

Table 2. Datasets available for localization tasks.

Dataset	Simulated Data/Measurements	Dataset Size	Signal Metric	Signal Type	Related Research Papers
JUIndoorLoc [14]	Real world data	25,364	RSSI	Wi-Fi	[26]
UJIndoorLoc [27]	Real world data	21,050	RSSI	Wi-Fi	[2,4,16,26,28–30]
IPIN 2016 [31]	Real world data	36,795	RSSI, magnetic, accelerometer, orientation	Wi-Fi	[30]
UTSIndoorLoc [4]	Real world data	9494	RSSI	Wi-Fi	[4,30]
DSI [32]	Real world data	1717	RSSI	Wi-Fi	[2]
UJI 2018 [33]	Real world data	63,504	RSSI	Wi-Fi	[2,12]
COMPASS [34]	Real world data	2310	RSSI	Wi-Fi	[2]
TAU [35]	Real world data	1428	RSSI	Wi-Fi	[2]
TAU additional [36]	Real world data	19,676	RSSI	Wi-Fi	[2]
TAU additional v2 [37]	Real world data	4638	RSSI	Wi-Fi	[2,4]
Alhomayani 2020 [38]	Real world data	12,000	RSRP and cell identity information	LTE	[38]
Aranda 2020 [39]	Real world data	10,737	RSSI	BLE	[39]
Outfin [40]	Real world data	>100,000	RSSI	Wi-Fi	[40]
			RSS	BLE	[40]
			RSRP	LTE	[40]
RadioLocSeer [3]	Simulated data	7920	RSS maps	Cellular	[3]
RadioToASeer [3]	Simulated data	7920	ToA maps	Cellular	[3]
Hoang 2019 [16]	Real world data	365,000	RSSI	Wi-Fi	[41]
Comiter 2017 [42]	Real world & simulated data	2184	AoA	5G	[42]
Koutris 2022 [43]	Simulated data	22,050	RSSI	BLE	[43]

Reference signal received power (RSRP); Time of arrival (ToA); Angle of arrival (AoA).

UJIndoorLoc [27] is one of the most commonly used datasets in wireless localization studies. It contains measurements in 3 buildings and 4 to 5 floors for different indoor environments. It also involves multiple devices and users in the data collection phase to add more variety. The authors of [27] extend their works in another domain in [33] by taking measurements at the same set of locations for 15 months. This dataset provides an option to test the robustness of DL-based localization methods against the signal variation in time domain, and also a possibility to explore the potential temporal correlation among different localization parameters. Besides these, UTSIndoorLoc [16] and IPIN2016 [31] include more data dimensions when building the datasets: the former one consists of measurements in 16 floors in a building, which provides higher data resolution in vertical dimension compared to most of the existing datasets. Ref. [31] collects other types of data, including geo-magnetic fingerprint and inertial sensor data, along side with the received signal strength (RSS) to enable the usage of data fusion techniques to enhance the localization accuracy. Datasets in [14,16,32,35–37] are also some of the fine-grained datasets collected in indoor space such as universities or labs, and can be used to test the performance of localization algorithms in different environments. In particular, the authors of [16,32,37] collect part of the data along some designed routes, which offers the researchers the chances to explore the trajectory prediction functionality of their DL-based models.

While most of the current available localization datasets are collected under Wi-Fi networks, [38–40,43] fill the gap by gathering measurements under LTE and BLE networks. In particular, both [39,40] also include measurements in outdoor scenarios, which can help to test the performance of outdoor localization methods. Moreover, although collecting real-world measurements to train and test the DL models seems to be the trend of most current studies, generating synthetic wireless data is always a potential option to save the data collection efforts and to ensure the amount of data needed during the training phase, and it has started to gain the attention in some of the recent research works. The authors of [3,42,43] simulate the wireless signal propagation environments via software implementation, and create the signal datasets in the predefined localization scenarios. The localization performances in the corresponding space are validated in their studies as well.

2.2. Data Preprocessing Methods

Learning directly from the raw signal data is generally challenging in a localization task due to several reasons: first of all, not all recorded values necessarily contain useful or even meaningful information during the data collection phase. When collecting a data sample or fingerprint for one location, a typical process is to record the signal data sent from a set of APs. However, usually only the signal sent from neighboring APs can be received.

Others can suffer from the pathloss, NLOS effect, or even interference in the environments, which usually leads to missing values or extremely low values in the measured data sample. In fact, these kind of data points can be the majority of each collected data sample, which can seriously slow down the convergence of the learning process. Secondly, the values of the input data for DL models are generally need to be bounded in some certain range, usually in [0, 1], in order to prevent training from diverging. Moreover, techniques like filtering, data transformation or augmentation can be effective to reveal the essential features in some certain scenarios. In this section, we aim to summarize those data preprocessing techniques that are applied in the recent works. Note that even though various of preprocessing methods are being used, there is no clear trend showing any of the methods outperforms the others in terms of localization performance. Therefore, here we include the methods, the types of data being processed, and the corresponding usage scenario to provide a reference for future studies, as shown in Tables 3 and 4.

Table 3. Data preprocessing methods for localization tasks.

Data Type	Preprocessing Methods	Data Format	Related Research Papers
RSSI/RSS	RSSI into greyscale images.	Image	[12]
	$\text{RSSI}_{\text{normalized}} = \dfrac{\text{RSSI}_{\text{original}} - \text{RSSI}_{\text{min}}}{\text{RSSI}_{\text{max}} - \text{RSSI}_{\text{min}}}$	Vector	[11,12,15,44]
	$\text{RSS}_{\text{normalized}} = \alpha + \dfrac{1-\alpha}{\text{RSS}_{\text{max}} - \text{RSS}_{\text{min}}}(\text{RSS} - \text{RSS}_{\text{min}})$	Vector	[11]
	A moving filter: $\text{RSS}'_i = \dfrac{1}{W}\sum_{j=0}^{W-1} \text{RSS}_{i+j}$	Vector	[5]
	$\text{RSS}'_i = \dfrac{\text{RSS}_i + 100}{\max(\text{RSS}) + 100}$	Vector	[28]
	Fill missing entries with -100 dBm	Vector	[26]
	$\text{Powed} = \begin{cases} 0, & \text{RSS}_i \text{ is None} \\ (\dfrac{\text{RSS}_i - \min}{-\min})^{\beta}, & \text{otherwise} \end{cases}$	Vector	[4]
	Average over all samples for each AP at different reference point.	Vector	[41]
	Standarized RSSI to zero means, and convert it to AoA: 1. $\theta = \cos^{-1}(\dfrac{\psi\lambda}{2\pi d})$ 2. $d = 10^{\frac{\text{RSSI}_{\text{ref}} - \text{RSSI}}{10n}}$	Vector	[43]
	Add a random number to each RSSI value according to their mean.	Vector	[45]
	Convert to 2D greyscale images.	Image	[3]
	1. Set unmeasured values to minimum minus 1. 2. Add the unmeasured values to all samples.	Vector	[2]
AoA	$\text{AoA}_i = \dfrac{1}{W}\sum_{j=0}^{W-1} \text{AoA}_{i+j}$	Vector	[5]
ToA	Min-max normalization	Vector	[15]
TDoA	Min-max normalization	Vector	[15]
CSI	Normalize to value of [0,1]	Vector	[46]
	Convert into time-domain CIR using inverse Fourier Transform. Keep the first channel tap. Then convert the CIR back to CSI using Fourier Transform.	Vector and image	[5]
	1. Transform CSI into polar coordinates. 2. Phase calibration for measured $\hat{\theta}$: $\theta(\mathcal{L}, n) = \hat{\theta}(\mathcal{L}, n) + \dfrac{2\pi i}{N_{\text{FFT}}}\delta - Z$	Vector	[47]
	2D Fourier Transform, and convert into 2D cartesion domain.	Image	[9]
	1. Convert frequency domain CSI to delay domain. 2. Computing autocorrelation matrix of the matrix got in previous step. 3. Vectorize and normalize the autocrrelation matrix.	Vector	[48]
RTT	Normalize to be in range of [0, 1]	Vector	[49]
CFR	Flatten raw CFR data into 2D images.	Image	[1]
FP amplitude	Min-max normalization	Vector	[15]
Occurrence of saturation	Min-max normalization	Vector	[15]

Access point (AP); Time of arrival (ToA); Time difference of arrival (TDoA); Channel impulse response (CIR); Fast Fourier Transform (FFT); Channel frequency response (CFR).

Table 4. Location data preprocessing methods.

Data Type	Preprocessing Methods	Data Format	Related Research Papers
Longitude & latitude	$\mathrm{lon}(S^*) = \mathrm{lon}(L^*) - (\mathrm{lon}(L^*) - \mathrm{lon}(R^*))\frac{d(L^*, S^*)}{\mathrm{long}(L^*, R^*)}$	Vector	[44]
	$\mathrm{lat}(S^*) = \mathrm{lat}(L^*) - (\mathrm{lat}(L^*) - \mathrm{lat}(R^*))\frac{d(L^*, S^*)}{\mathrm{long}(L^*, R^*)}$		
	$\mathrm{lon}_{\mathrm{normalized}} = \frac{\mathrm{lon}_{\mathrm{origin}} - \mathrm{lon}_{\mathrm{min}}}{\mathrm{lon}_{\mathrm{max}} - \mathrm{lon}_{\mathrm{min}}}$		
	$\mathrm{lat}_{\mathrm{normalized}} = \frac{\mathrm{lat}_{\mathrm{origin}} - \mathrm{lat}_{\mathrm{min}}}{\mathrm{lat}_{\mathrm{max}} - \mathrm{lat}_{\mathrm{min}}}$		
	Subtract by mean	Vector	[2]
2D coordinates	$X_{\mathrm{normalized}} = \frac{X - X_{\mathrm{min}}}{X_{\mathrm{max}} - X_{\mathrm{min}}}$, for both x, y coordinates.	Vector	[11]
Distance from longitude & latitude	$C = \sin(\mathrm{lat}A)\sin(\mathrm{lat}B) + \cos(\mathrm{lat}A)\cos(\mathrm{lat}B)\cos(\mathrm{lon}A - \mathrm{lon}B)$	N/A	[44]
	$\mathrm{distance} = R\frac{\arccos(C)\pi}{180}$		

S*, is the sampling point location. L*, and R* is the reference point at the left and right end of the building.

Normalization is one of the most commonly used preprocessing techniques in DL-based localization. As we mentioned earlier, it is necessary in most of the cases to shift the range of the signal data. Also, it can help to increase the resolution of the received data to further highlight the essential measurement data points. Min-max normalization is a typical choice and has been used in processing different types of data including Received Signal Strength Indicator (RSSI) [4,11,12,44], time of arrival (ToA), time difference of arrival (TDoA), first path (FP) amplitude, occurrence of saturation [15] and the location data (longitude and latitude) [11,44]. It is also deployed as the first step before any further data processing [12]. Some of the variants of min-max normalization have also been developed. In [11], a predefined factor α is introduced to normalize the non-zero signal strength into the range of [α, 1]. Song et al. transform the raw RSS data into a powed form to increase the localization performance [4]. Powed or even exponential representations of RSS data are considered to be more informative than other representations like positive representation and zero-to-one normalization [4,50]. Computations in the powed transformation introduce the non-linearity into the relation between the RSS values and the distance. In this way, the RSS values received at close range can be more distinguishable than the ones received at long distance. Since the signal received from the longer range is more likely to be fluctuated and can include higher randomness, it is considered to be less informative. Thus the powed representation can focus more on the RSS values from closer distance. In addition, another advantage of introducing this non-linearity is that, the variation of RSS values is more noticeable when the RSS values are high comparing to the values in a linear scale [50]. As the result, the RSS values can reflect more detailed spatial information when the RSS values are large enough. Meanwhile, the variation of powed RSS values at lower range becomes negligible, and hence can prevent the randomness from jeopardizing the learning of DL models. These provide an intuition on why some RSS representations like powed representations outperform other linear representations in localization tasks. In fact, the min-max normalization can be considered as a combination of positive and zero-to-one normalized representations, and thus still maintains the linearity from the raw RSS data. The readers can refer to the analysis in [50] for more details regarding different distance functions and data representations used in localization problems.

Besides shifting the range of the data, how to compensate the missing or unmeasured data points has also been studied in the recent works. For the RSSI data, the value of each valid data point usually can varies from -150 to 0 dBm, while the bounds can be slightly different in different application scenarios. In [26], all the missed data points are filled with -110 dBm, while the range of the RSSI measurements is [-100, -11] dBm, to be distinct from the minimum value. A similar approach is mentioned in [2]. On the other hand, the undetected values are set to 0 in [4]. The authors in [28] simply add 100 to all signal strength values before normalization to compensate all the negative-value entries.

Preprocessing of channel state information (CSI) tends to be more complex as it generally involves data transformation in different domains to eliminate the interference or errors occurring during signal transmission. It is also considered to be a necessary step for DL-based methods because raw CSI data can be affected by various factors such as channel conditions or hardware imperfection, which brings more challenges to the learning process [48]. Ref. [5] designs a three-steps filtering and phase calibration process to remove interference from other Wi-Fi APs and mitigate the effect of multipath fading. In [48], the frequency-domain CSI is transformed into delay-domain via discrete Fourier Transform (DFT). Then the autocorrelation matrix is calculated to alleviate the effect caused by synchronization errors, carrier frequency offset or phase noise. Finally, the preprocessing process finishes with a real-valued decomposition and normalization to serve as the needs of DL models. The authors further enhance the localization performance by combining consecutive CSI features and CSI probability maps in time domain to track the movement of target. With all these preprocessing steps, the proposed method in [48] is able to achieve sub-meter-level mean distance error in both LOS and NLOS scenarios. The collected CSI data is transformed into polar coordinates in [47] to enable further phase calibration step in order to remove the random jitter and noise caused by hardware malfunction. Noise reduction is another crucial step in processing raw CSI data to improve localization performance. Filtering has been proven to be an effective and common strategy in noise reduction and outlier removing. In [51], Kalman filtering is integrated with a Gaussian Mixture Model (GMM) to reduce the noise in the CSI data. The authors in [52] applied Hampel filter and wavelet filter in order to eliminate data outliers and reduce noise. Besides filtering, [53] proposed a KNN-based algorithm to for removing significant data outliers. The studies presented in [54] implemented a noise and dimension reduction approach where polynomial regression is applied for noise filtering.

Transforming the raw data into images is another direction of data preprocessing which can compose 2D radio map to better reveal the spatial features. This type of approaches also allows the utilization of those compelling image processing algorithms in DL to further exploit the location information from the data. Chen et al. [12] convert the normalized RSS matrix into a greyscale image, in which the signal strength received at the reference point is encoded in the pixel color, thus indicating the distance between the reference point and surrounding APs and represent the location information of a coordinate. Yapar et al. [3] incorporates the greyscale images and the black-white images which depict the environment layouts and base station locations as the input features of their DL model. In [1], the raw channel frequency response (CFR) data is transformed into an image for each antenna pair in multiple-input and multiple-output (MIMO) system to highlight the angle of arrival (AoA) information which is closely related to the positional information. The authors in [9] build a 2D heatmap using the AoA and time of flight (ToF) information extracted from the raw CSI data to alleviate the randomness on the CSI data caused by the environmental changes.

In addition to these, the authors of [43] transform the RSSI data to AoA to enable the usage of the built-in BLE direction finding function for localization. When processing the RSSI data, they also propose a method which eliminating the absolute phase value, but keeping only the values of relative phase difference to the first antenna, in order to improve the AoA estimation and also reduce the dimension of input data. Averaging the RSSI samples is another approach to reduce the small-scale fading effect in the raw measurement [3,12,41]. Moreover, normalization and transformation of the location information is also crucial in training the DL model. Table 4 includes a few of the methods used in the existed studies, including how to calculate the distance between different nodes according to their measured longitude and latitude data.

2.3. DL Algorithms

Since DL algorithms demonstrated the power in image classification few years ago, they have been widely adopted in many other applications including localization. The stacked multi-layer architecture enables models like neural network (NN) or convolutional neural network (CNN) to extract the characteristics from wireless signal data. The mapping from an input data to a location is learned through a data-driven process to increase the robustness of the location algorithms. This learning process also makes the location estimator more adaptive to the signal variations or changes of environments because the DL model can be updated with additional data. Compare to traditional range-based or range-free localization methods, DL model does not rely on hand-crafted features or prior assumptions of statistical signal modeling [5]. In this section, we focus at each type of algorithms used for localization and how these are implemented and adopted in different scenarios, and especially what types of input data is processed as shown in Table 5.

2.3.1. DNN

Deep neural network (DNN) is an extension of NN model used to capture more complex features by stacking more layers. It has been demonstrated to be an effective solution in processing various localization data and is one of the commonly used DL algorithms in this area. Refs. [11,29,46] all develop a six-layer DNN architecture to estimate the coordinate from signal data directly. Various DNN-based localization models are also considered to improve the localization performance or provide additional functionalities. The authors in [44] propose a two-stage DNN model to achieve both floor classification and coordinate estimation. DNN with different number of layers are implemented in [5] for different indoor room settings and input data types. Lu et al. train the DNN with six different types of input data and combine the outputs of six classifier to improve the localization accuracy [15]. Comiter et al. integrate multiple multi-layer perception (MLP) architectures together to process the phase information measured at different base stations

https://doi.org/10.53941/aieng.2026.100001

and combine them to produce the final location estimation [42]. Similarly, [43] design a hierarchical MLP model to fuse the data collected on multiple channels. Unlike conventional DNN-based localization algorithms which predict the coordinate of the location, the authors of [41,48] modify the DNN models to produce the distribution of data sample at each reference point in the environments, and then to infer the location information based on that.

Table 5. DL algorithms for localization tasks.

Algorithm	Input Data	System Type	Related Research Paper
DNN	AoA	5G, Wi-Fi	[5,42]
	CSI	Wi-Fi	[5,46,48]
	RSSI	5G, Wi-Fi, BLE, UWB,	[11,15,29,41,43–45]
	ToF	5G	[29]
	I/Q data	BLE	[43]
	ToA	UWB	[15]
	TDoA	UWB	[15]
	CIR	UWB	[15]
CNN	RSSI	Wi-Fi, cellular, BLE	[2,4,5,12,38,45]
	CSI	Wi-Fi, 5G	[5,47,55]
	CFR	5G	[1]
	Magnetic field and intertial sensor data	Wi-Fi	[38]
	CSI	Wi-Fi	[5]
	ToA	UWB	[56]
	RSSI	Wi-Fi	[16]
Autoencoder	RSS	Wi-Fi	[4,28]
	AoA and ToF	Wi-Fi	[9]
	RSRP	LTE	[38]
DRL	RSSI	Wi-Fi	[30]
GAN	CSI	Wi-Fi	[57]

In-phase and quadrature: (I/Q); Generative adversarial network (GAN).

2.3.2. CNN

CNN is another type of multi-layer DL architecture. Comparing to DNN, it has the advantage of capturing the correlation between the neighboring input features of the same layer. Being the backbone of many existing image processing algorithms, CNN is a natural choice to handle the localization data that can be transformed into an image form. The authors of [12] implement a CNN-based model to predict location from the grayscale image transformed from RSSI data. Gao et al. propose a CNN architecture to capture the signal behavior in adjacent channels from CFR images [1]. In addition to image, CNN is also suitable for processing the data in 2D matrix. In [47,55], a CNN-based model is designed to estimate location information from 2D CSI matrix. Although primarily used for image processing, CNN has also proven to be effective in dealing with sequence data in wireless communications issues, including wireless localization. 1D-CNN layers are implemented in [2,4] to predict the location coordinate from a RSSI vector. Wisanmongkol et al. develop both 1D and 2D-CNN-based models and compare the localization performance under different scenarios.

2.3.3. RNN

Recurrent neural network (RNN) is usually considered to be a better fit to process wireless signals, because it has the advantage of capturing the sequential correlation of the data. This property also makes RNN a suitable solution in predicting the location based on time-dependent measurements. In [56], RNN-based algorithms are trained to predict the trajectory of the moving targets. Hoang et al. propose five different RNN models to support input and output in different length in order to achieve both location and trajectory prediction [16]. The authors of [5] also implement both single-layer and multi-layer LSTM models to estimate the location information from CSI data.

2.3.4. Autoencoder

Unlike previously discussed algorithms, autoencoder (AE) is trained with an unsupervised way in which the target of training is usually the data itself or a transform of it. The goal of autoencoder is to compress the original input data into a latent representation which contains enough information to reconstruct the target one. In [4], the AE architecture is used as a feature extractor to capture the fingerprint characteristics. These information are feeded into a CNN or DNN model to finish the location estimation. In addition, adding random noise to the input data is a common technique in implementing AE to force the model learning the essential feature from the corrupted data. This idea is adopted in [28] to further enhance the localization performance. The authors of [9] propose a AE with one encoder and two decoder, while one decoder is trained to reconstruct the heatmap for the surrounding environments, and the other one to the image revealing the location information.

2.3.5. Others

With the revolution of DL algorithms, more and more advancing models have also been developed for localization purposes. For example, Ref. [30] models the localization problem into a Markov decision process, and implement a deep reinforcement learning (DRL)-based algorithm to tackle the 3D localization problem. The authors of [57] utilize the generative adversary network (GAN) to generate CSI data to support the training of the localization model.

2.4. Wireless Localization Simulators

While many of the localization studies choose to collect the data though wireless communications devices in a real-world space, simulating the signal transmission environments to gather the data is still a common approach, especially when implementing DL-based localization algorithms. A sophisticated simulator provides the freedom of emulating the signal propagation in an arbitrary or dedicated environment. It also offers the amount and variety of the data in order to develop the DL models. Using a software platform allows to manipulate the settings or parameters of a wireless communications system to generate the signal data in different scenarios. It can also save the effort in data collection and ensure that the DL model is trained and tested with sufficient amount of data. In Table 6, we list the simulators that are able to model the localization scenarios in different wireless standards.

Table 6. Simulators for localization tasks.

Source Article	Signal Type	Software Platform	Remarks
[42]	5G	Python	Support both 2D and 3D simulation
[58]	5G	Matlab	CSI-based localization
[59]	Cellular and Wi-Fi	Python	Enable simulating signal propagation and designing of the environments; include an interactive interface.
[60]	BLE	Matlab	BLE direction finding; support both 2D and 3D localization.
[61]	UWB	Matlab	UWB localization using TDoA.
[62]	BLE	Matlab	AoA and AoD based direction finding.
[63]	LTE	Matlab	TDoA-based localization.
[64]	Wi-Fi	Matlab	ToA-based localization.
[65]	ZigBee and UWB	Matlab	N/A
[66]	5G	Matlab	TDoA-based localization.
[67]	Wi-Fi	Matlab	CSI-based localization.

Winprop [59] is a software used to simulate the signal propagation in various environments. It enables the designing of a propagation space and thus can help to create a detailed localization scenario. It also includes modules to support the planning under heterogeneous wireless standards such as Wi-Fi, LTE, and 5G. As one of the most commonly used software platform in wireless communications, Matlab also provides various of toolbox for localization studies in those commonly deployed wireless standards, including Wi-Fi [64,67], LTE [63], 5G [66], ultra-wideband (UWB) [61], BLE [60,62] and ZigBee [65]. The authors in [58] develop a CSI-based localization platform using Matlab, which support both sub-6GHz and millimeter wave (mmWave) operating behavior. Moreover, Comiter et al. [42] build a simulator using Python to model the 5G communication environments and can generate ToF and AoA data for localization tasks.

3. Localization Using Wi-Fi Systems

Implementing a localization system under the Wi-Fi networks is one of the most popular choices, especially for the indoor localization applications. The localization functionality can be implemented in the existing Wi-Fi infrastructures and devices to save the deployment cost. On the other hand, the localization performance is affected by various factors including the NLOS and multipath effect, fading, signal fluctuation, moving target or objects, and environmental variations, etc. [4,30,31]. Existing research and studies focus on improving the localization accuracy by mitigating the effect brought by these challenges in the current Wi-Fi localization system. In this section, we summarize how DL algorithms are applied in Wi-Fi-based localization tasks to handle those challenges. In particular, we compare the works according the types of localization data used as the input, including RSSI, round trip time (RTT), CSI, and AoA as listed in Table 7. Different wireless data reveal the location information in different ways and they all have their own advantages and shortcomings in a specific localization scenarios.

Table 7. Summary of Wi-Fi based localization.

Data Format	Data Representation	DL Algorithm	How DL Is Used	Dataset	Performance	Remarks	Source Article
RSSI/RSS	RSSI, mean and variance	Learning based method (BayesNet, SVM, KNN and K*)	Fingerprint based using RSSI	JUIndoorLoc and UJIn-doorLoc	For JUIndoorLoc, 80% of error using BayesNet and KNN are within 5 m; 80% of the error are within 3 m using SVM, and 80% of the error are within 3.6 m using K*.	Weighted ensemble approaches	[26]
	RSS, fingerprinting	DNN and stacked denoising auto-encoder, probabilistic model	Feature extraction and denoising using RSSI	UJIndoorLoc and real world data	1. For UJIndoorLoc, 94.6% accuracy in floor recognition, and average position error is 5.29 m; 2. For self-collected dataset, 2.13 m average position error in dynamic positioning, and 1.22 m in static positioning.	Static and dynamic trajectory estimation	[28]
	Images of RSS	CNN and support vector regression (SVR)	Fingerprint based using RSSI	UJI's library	85% of the error are within 3.46 m, and 65% of the error are within 2.45 m.	N/A	[12]
	RSSI	Deep reinforcement learning	Dynamic decision making process using RSSI	IPIN2016, UTSIndoor-Loc, UJIndoor-Loc	Multi-floor: 1. In UJIndoorLoc, 75% of the error are within 0.188 m; 2. In UTS, 80% of the error are within 0.219 m. Single floor: 1. In IPIN, 75% of the error are within 1.97 m; 2. In UJI, 75% of the error are within 0.197 m.	Include all single floor and multifloor performance; UTSIndoor covered 16 floors including 3 basement levels.	[30]
	RSS, AoA, CSI and hybrid	FNN, 1D-CNN, 2D-CNN, and LSTM	Fingerprint based regression and classification; range-based using RSS and AoA, range-free using RSS and CSI	Real world data	1. In closed-room, average position error is 1.86 m. 2. In corridor, average position error is 3.18 m.	Ensemble of different data format.	[5]
	RSS	DNN	fingerprint based using RSSI	Real world data	1. Wi-FI only: 0.19–0.44 m. 2. Cellular + Wi-Fi: 0.17–0.41 m.	Consider Wi-Fi and cellular	[44]
	RSS	DNN	Fingerprint based using RSSI	Real world data	1. For self-collected dataset, 75% of the error are within 1.82–2.69 m. 2. For dataset in [16], 75% of the error are within 1.03–1.39 m.	Consider different # of APs, and RPs, also different # of RSS samples.	[41]
	RSSI	RNN	N/A	Real world data	80% of the errors are within 1 m.	Trajectory position	[16]
	RSS	CNN and transfer learning	Fingerprint based using RSSI	Real world data	Mean error varies from 1.82 m to 29.352 m in different dataset.	Training using 15 Wi-Fi RSS datasets	[2]
	RSS	CNN	N/A	Real world data	1. For UTSIndoorLoc, 94.57% in floor recognition with a mean error of 7.6 m. 2. For UJIIndoorLoc, 96.03% in floor recognition with a mean error of 11.78 m. 3. For Tampere, 94.22% in floor recognition with a mean error of 10.88 m.	Dataset available	[4]
RTT	ToF, and rount trip time	Deep learning and probabilistic location estimator	Fingerprint based using RTT	Real world data	Median error <0.75 m	Synchronization not required, impact of AP density	[49]
CSI	2D heatmap of AoA and ToF	Autoencoder	Fingerprint based using CSI	Simulator and real data	Median accuracy of 65 cm; 91 cm median error in unknown environment,	Consider relocated furniture and reflectors, different bandwidth	[9]
	CSI: amplitude and phase	Logistic regression and DL, also computational methods to increase robustness.	Fingerprint based using CSI	Real world data	Median error 0.97 m	N/A	[68]
	CSI: amplitude and phase	N/A	Fingerprint based using CSI	Real world data	Median error 0.972 m	N/A	[47]
	CSI	DNN	Fingerprint based using CSI	Real world data	70% of the error are under 1.7 m.	N/A	[46]
	RSS, AoA, CSI and hybrid	FNN, 1D-CNN, 2D-CNN, and LSTM	Fingerprint based regression and classification; range-based using RSS and AoA, range-free using RSS and CSI	Real world data	RMSE$\sim$2m.	N/A	[5]
	CSI	GAN for data generation, 1D-CNN-LSTM for learning	Fingerprint based using CSI	Real world data	90% of the positioning errors are within 1.43 m.	Consider distance between Aps that affecting the correlation of CSI. Consider mixing both simulated and real-world data in training.	[57]
AoA	RSS, AoA, CSI and hybrid	FNN, 1D-CNN, 2D-CNN, and LSTM	Fingerprint based regression and classification; range-based using RSS and AoA, range-free using RSS and CSI	Real world data	1. In closed-room, average position error is 1.86 m. 2. In corridor, average position error is 3.18 m.	Ensemble of different data format.	[5]

Support vector machine (SVM); K nearest neighbor (KNN); K* is an instance-based learner using an entropic distance measure; Indoor positioning and indoor navigation (IPIN); Reference points (RPs); Forward neural network (FNN); Root mean square error (RMSE); Long short-term memory (LSTM).

3.1. RSSI

RSSI is one of the most easily obtained localization data. It can be used to estimate the distance information to neighboring APs or construct radio map to reveal the location of the reference point in the space. The general work flow of a RSSI-based localization system is depicted in Figure 3. However, RSSI can be largely affected by interference signal or any signal fluctuation caused by other factors such as hardware imperfection [14]. Also, obstacles and multi-path effect are also the reason that the collect RSSI data cannot accurately represent the location information [69]. Therefore, existing studies attempt to resolve the related issues from different aspects. As highlighted in Figure 3, the DL algorithms can be applied in the feature extraction process to enhance the spatial information hidden in the raw RSSI data, as well as in the location prediction domain to further explore the correlation between the extracted RSSI fingerprint and the location information. The authors in [28] adopt a stacked-denoising autoencoder structure to improve the feature extraction from RSSI fingerprint. A constrained Kalman filter and hidden Markov model are implemented to alleviate the RSSI fluctuation and uncertainty due to the movement of the user that are being localized. Chen et al. focus on improving the runtime efficiency of the CNN-based localization model to fit need of real-time localization. Dou et al. model the localization process as a sequential decision making process using Markov decision process (MDP), and train a DRL algorithm to enable it perform the localization operation through searching the space, and thus accommodating the environmental variations on the RSSI data [30]. The authors in [5] combine the multiple DL-based model trained with different types of data, including RSSI, to fit the localization tasks in different indoor space. Similarly, Zhang et al. [44] implements one DNN model for floor-level classificaiton followed by three different DNN models for coordinate estimation in three different floors. In order to resolve the ambiguity of RSSI data, Hoang et al. propose a RNN-based algorithm that combines RSSI measurements in sequential locations to enhance the localization accuracy [16]. State-based modeling is also considered in [41] to predict the location of user from the preceding positions, and thus enable the localization of moving target or trajectory prediction. The DNN model in this work is trained to capture the distribution of RSS measurements at each reference points rather than learning the mapping from the signal strength to the coordinates directly, in order to denoise the RSS data. The localization efficiency in terms of the length of RSS samples used as the input of the model is also studied in [41]. Klus et al. pretrain the model with 15 RSSI localization datasets to improve the adaptivity to different environments. The proposed model is then fine-tuned with individual dataset for location estimation in the corresponding indoor space [2]. In addition, the authors of [4] integrate an AE and 1D-CNN architecture to help extracting features from RSSI data suffering from noise and multi-path effect.

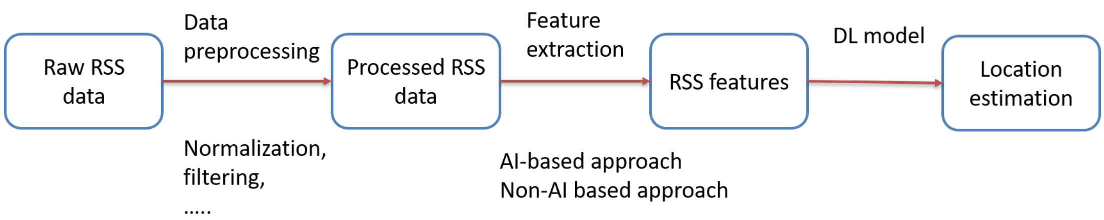

Figure 3. A RSS-based localization system using DL

3.2. RTT

In order to overcome the shortcomings of using RSSI, time-based data has also been studied for localization tasks, including round trip time (RTT). RTT-based methods log the time which the localization signal takes to travel between the target and the APs, and infer the distance information accordingly. In this way, the data suffers less from the fluctuation or attenuation of the wireless signal, and experience less affect by environmental changes like multi-path interference. However, this type of method has its own shortcomings. The RTT measurement generally requires accurate synchronization between multiple devices [58]. Thus, synchronization errors will unavoidably introduce errors in the localization step. In [49], the authors proposed a DL-based system without requiring a synchronization block, and is able to mitigate the effect of environmental variation or interference.

3.3. CSI

Channel state information (CSI) is another representation of wireless signals which includes frequency-domain information and also contains signal information in multiple channels. Therefore, it is usually considered to have a more complete location profile than RSSI data and is also a more stable representation [46,57]. Meanwhile, as summarized in Figure 4, raw CSI data generally requires additional transformation or preprocessing steps in order to reveal the spatial information, and reduce the interference or errors on the raw data. Similar to RSSI-based methods, related works in CSI-based localization also focus on utilizing DL algorithms in two stages: first, in the CSI feature construction stage to translate the raw CSI data into proper format which contains more spatial information; and second in the location prediction stage to improve the accuracy and robustness. In [9], the authors use 2D FFT to extract AoA and ToF information from raw CSI measurements, which is then trained to reveal both the target location and the surrounding environmental information. The authors of Refs. [47,68] focus on enhancing the robustness of CSI-based localization system by adding a perturbation to the training dataset. Wisanmongkol et al. transform the CSI into different dimension to fit different DL algorithms for performance comparison [5]. Zhang et al. [57] concatenates LSTM and CNN architectures to capture both spatial and temporal information from CSI data. On the other hand, collecting CSI data usually requires specialized hardware and the raw data often needs several preprocessing steps before analyzing the location information [41,49]. Therefore, CSI-based localization methods can be time consuming and with a large computation overhead. Improving the efficiency of processing the CSI data is also a focus of some of the current studies [46].

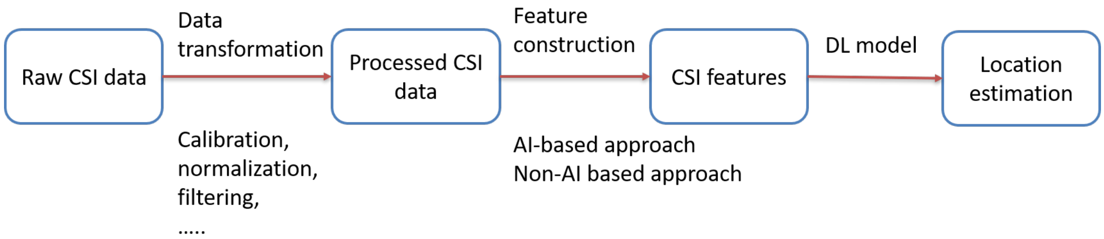

Figure 4. A CSI-based localization system using DL

4. Localization Using Cellular Systems

Cellular signal-based localization system is another promising solution to the various applications. It can utilize the existing cellular-service infrastructures and mobile devices. Most importantly, it can provide wider coverage than Wi-Fi based systems especially in outdoor and urban environments. With the advancing and deployment of 5G networks, the technologies such as mmWave and massive multi-input multi-output (massive MIMO) enable the data capturing in a higher resolution to provide more accurate (e.g., centimeter level) localization service [42,70–72].

On the other hand, localization in 5G networks can also be affected by some of the environmental factors such as NLOS [73,74]. Current studies approach and resolve these challenge by adopting DL-based algorithms. In this section, we summarized the existing related research works in Table 8 from both the data and algorithm perspective, while also highlight the application scenarios and performance achieved by each of the studies. The authors of [73] propose a NN and random-forest based algorithm to localize a moving target in urban area, where NLOS condition frequently occurs. Yapar et al. [3] integrates the location information of the base stations (BS), the estimated radio map of the area, together with the RSS data to provide a location estimation in a simulated urban area. Comiter et al. develop a DNN-based method for localization in both indoor and outdoor area. The proposed method is able to handle the potential collinearity problem when collecting angle information from multiple BS which are aligned in a straight line, and also the multi-path effect in the indoor environments. Gao et al. develop a CFR data-generation scheme and the preprocessing methods to capture the features from a multi-antenna setup, as well as improve the robustness of the algorithm [1]. In [44], the authors implement a localization algorithm which is trained using the data collected in Wi-Fi, cellular networks, and the fusion of both, and then compare the performance of different setups. Moreover, Arnold et al. [75] aims at improve the indoor localization performance in both LOS and NLOS indoor scenarios, and demonstrates that their proposed methods can achieve sub-meter level accuracy in both circumstances.

Efficiency is another main concerns in localization tasks in cellular networks, especially when DL-based methods are deployed. The data collection process is usually time and labor consuming. Also, it is necessary and challenging to ensure that the collected data completely represent the complexity of the environment, especially in indoor space. Therefore, many research and studies focus on approaching the localization problem from this direction. Both the authors of Refs. [76,77] consider cooperating a GAN architecture with the localization model. The GAN-based model can be trained to generate artificial radio map or fingerprint to reduce the amount of real world measurements needed during the training of the localization model. Experiments also indicate that including both real and synthetic data in training can further improve the localization accuracy. Tarekegn et al. [77] further validates that only a relative small amount of real data can be sufficient to provide a reasonable localization accuracy, and thus the data collection and environment survey efforts can be largely reduced. Localization efficiency in terms of latency and the number of training data is also investigated in [42]. Currently, DL-based localization method is

https://doi.org/10.53941/aieng.2026.100001

still being explored and is becoming a potentially important part of the future high-precision localization service [78] in cellular networks. In addition, using the ray-tracing tools and software are also shown to be effective in modeling the cellular networks and environments to simplified the data collection process [79,80].

Table 8. Summary of cellular system based localization.

Data Format	Data Representation	Signal Type	DL Algorithm	Dataset	2D/3D	Performance	Remarks	Source Article
Signal strength	RSS and ToA	Wi-Fi cellular	DNN	Simulated data	2D	MAE varies from 4.8 m to 19.6 m in different environment.	Use Winprop to simulate signal propagation.	[3]
	RSS	Wi-Fi cellular	DNN	Real world data	2D + floor identification	1. Cellular only: mean error is 3.7–4.3 m. 2. Cellular + Wi-Fi: 0.17–0.41 m.	Consider Wi-Fi + cellular.	[44]
	Beam reference signal received power (BRSRP) and distance of departure (DoD)	5G	Neural network and random forest	N/A	2D	80% of the error are within 10 m.	N/A	[73]
	RSSI	LTE	GAN	Real world data and simulated data	2D	1. Indoor: margin error within 0.4 m. 2. Outdoor: margin error within 10 m.	Use srsLTE to simulate LTE network.	[76]
	RSS	Wi-Fi cellular	GAN and LSTM	Real world data and simulated data	2D	Mean distance error: 0.47 m. 88.95% of the error are within 1 m.	Combine both synthetic radio map generated by GAN and real world data in training.	[77]
	RSRP	5G	DNN and decision tree	Simulated data	3D	Mean distance error 1.4 m.	Build ray-tracing model using WinProp.	[79]
AoA	AoA	5G	DNN	Both synthetic data and real world data	2D	1. When using only real data in training, median squared error varies from 0.74 m to 1.2 m. 2. When using both real and synthetic data in training, median squared error varies from 0.33 m to 0.76 m.	Consider training using synthetic data or measured data.	[42]
ToA	RSS and ToA	Wi-Fi cellular	DNN	Simulated data/available software	N/A	MAE varies from 4.8 m to 19.6 m in different environment.	Use Winprop to simulate signal propagation.	[3]
CFR	CFR image	5G	DNN	Real world data	3D	1. In indoor scenario, 90% of the error are within 0.51 m. 2. In urban canyon, 90% of the error are within 0.36 m.	N/A	[1]
CSI	Raw CSI data	5G	CNN	Real world data	3D	Mean distance error ∼0.75 m in LOS; ∼0.95 m in NLOS.	N/A	[75]
	AoA, delay, received power and ToA	6G	LSTM	Simulated data	3D	Mean distance error: 0.27 m in NLOS	Build ray-tracing simulation model using Wireless InSite	[81]

Mean absolute error (MAE).

Moreover, it is envisioned that the developing of future 6G communications is targeting at bringing the wireless localization service into a next level. While featuring with technologies like THz communications and extremely-large scale multiple-input multiple-output (XL-MIMO), 6G network is expected to enable the deployed localization service to deliver lower-latency and sub-centimeter level precision performance because of its advantages such as high-speed data transmission or accurate beamforming [82,83]. Furthermore, the massive connectivity provided by the 6G communications can potentially catalyze the support the joint communications and sensing (JCAS) framework. With this widely deployed and coordinated network infrastructure, the scale and performance of localization service can be further enhanced to support various of next generation applications such as UAV surveillance, precision agriculture and traffic monitoring [84].

On the other hand, those advancing technologies in 6G communications also introduce challenges to localization performance. THz communications can lead to less robustness of localization in NLOS scenarios and will suffer more severe multipath effects. In addition, the channel characteristics of each antenna on a XL-MIMO system can have a high variance due to its location or orientation, thus cause the challenge on high-precision localization [82]. Recent research and studies have started to focus on resolving these issues by using DL algorithms. In [85], an attention-based network was proposed to alleviate the NLOS and multipath effects from the CSI data in a MIMO system. The authors in [82] adopted a CNN-based architecture to address the spatial non-stationarity and for noise reduction. The proposed method is also shown to be effective in revealing the spatial information to provide accurate location estimation. Moreover, Pan et al. develop a foundation model for localization in [86]. They further demonstrate that the knowledge from that large foundation model can be transferred into a lightweight model to perform localization service in single or across multiple device or infrastructures. Nevertheless, the utilization of DL algorithms on localization in 6G networks is still far from being fully investigated. But the integration of DL with localization application is undoubtedly one of the main direction in the future 6G networks.

5. Localization Using Other Wireless Systems

Localization based on other wireless standards besides Wi-Fi and cellular networks has also been investigated to provide the service in different scenarios. UWB and BLE are the standards that are commonly deployed in indoor and outdoor applications, and thus can be utilized to provide localization services with the deployed devices. Besides, IoT standards are also the viable choices. A system like radio frequency identification (RFID) or ZigBee has the advantage in managing connections for sensors or devices, which is the foundation of the tracking or monitoring applications [44,87]. On the other hand, those systems also have their constraints due to the unique signal properties, which limit them from wide deployment as Wi-Fi or cellular systems [88]. In this section, we will discuss about the advantages and drawbacks of UWB and BLE based localization methods. We also summarize some of the features of existing studies in Table 9 for the comparison.

Table 9. Summary of UWB and BLE based Localization.

Environment	Data Representation	DL Algorithm	Dataset	2D/3D	Performance	Remarks	Source Article
UWB	RSSI, ToA, TDoA, first path amplitude, and CIR	LSTM and DNN	Real world data	2D	1. Indoor positioning with mean error of 0.02 m. 2. Indoor tracking with mean error of 0.08 m.	Consider fusion of different features.	[15]
	Raw signal	LSTM	Simulated data	N/A	Mean error of 0.07 m.	N/A	[56]
	CIR	CNN	Real world data	2D + 3D	Mean error varies from 0.113m to 0.65m depending on the number of anchor nodes used.	Channel classification and ranging error regression.	[89]
BLE	RSSI and I-Q data	DNN and CNN	Simulated data	2D	1. When the funiture is high, mean error varies from 0.61 to 1.03 m. 2. When the furniture is low, mean error varies from 0.69 to 1.3 m.	Estimate angle from RSSI value. Use WinProp.	[43]
	RSSI	ResNet and DNN	Real world data	2D	Positioning accuracy $\sim$97%.	N/A	[45]
	RSS	CNN, LSTM and GAN	Real world data	2D + floor number	1. Mean distance error varies from 0.74 to 2.18 m across different Wi-Fi datasets/ 2. Mean distance error $\sim$0.94 m in two BLE datasets.	Use GAN to generate synthetic data to improve performance.	[90]

Residual network (ResNet).

5.1. UWB

UWB based localization systems are able to achieve centimeter level accuracy because of its high data rate and nanosecond-level resolution in time-domain measurements [15,91]. In addition, the property of having large bandwidth helps to improve its immunity to multipath effect. However, the resulting weak signal penetration becomes the reason why UWB-based localization suffers in NLOS environments [92]. The infrastructure and hardware cost is another burden which stops UWB from being widely applied like Wi-Fi or cellular standard [5]. Existing research has focused on how to extend the usage of UWB for localization in NLOS environments while maintaining a satisfactory level of performance. Poulose et al. [56] propose a multilayer LSTM-based method to better capture the location information from the ToA data and improve the performance in NLOS scenarios. The authors in [89] implement a CNN-based algorithm to exploit the location data from channel impulse response (CIR), which is considered to be less suffering from the NLOS effect in the environment compared to conventional time-based data. Lu et al. [15] integrate multiple DL-based models which are trained using different types of data to enhance the localization accuracy. Despite of being able to provide high precision, UWB-based localization requires dedicated devices or hardware components, which can greatly raise the cost of the deployment. Meanwhile, this will also prevent the UWB-based localization from being widely used, as most of the common devices or infrastructures do not have the corresponding function blocks embedded within [39].

5.2. BLE

BLE is usually used as a energy efficient wireless standard for short-distance communications. Bluetooth signal characteristics largely limit its coverage area and usage in outdoor space [5]. The multi-path effect or fading deteriorate the BLE signal more than they do to many other wireless signals such as UWB or Wi-Fi [43]. However, it can still be utilized in many indoor scenarios, and enables more portable localization services. Koutris et al. [43] proposes a CNN and DNN-based hierarchical architecture to fuse the data collected from different channels to improve the localization accuracy in the NLOS environments. The robustness of the proposed method is tested under several simulated indoor environments where different number of furnitures are placed in the space to emulate various levels of NLOS effect. Liu et al. [45] includes a ResNet architecture in the developed model to help the feature extraction from BLE fingerprint. In [90], the authors design a GAN-based synthetic radio map generator to cooperate with the localization model to further improve the localization accuracy. The model is forced to learn the most relevant spatial information from the raw input fingerprint and then to generate an enriched version of fingerprint to better serve for the localization process.

6. Challenges and Future Directions

Precision and time-efficiency are always the prime concerns in practical localization applications. While most of the existed localization studies limit the error around 1–10 meters, sub-meter and even centimeter-level accuracy are becoming the major pursue of some of the current research in order to satisfy the needs of future applications such as IoT factory, IoT farm, robotics or drone monitoring and tracking [6,93]. Low run-time or latency is another important challenge for providing real-time localization services. As for DL-based localization methods, quantity and quality of training data, as well as the efficiency of data collection are the foundations of a localization system. Therefore, in this section, we highlight some of the existing works which tackle the sub-meter level precision, latency and data engineering issue through DL-based techniques.

6.1. Sub-Meter Level Localization

Traditional KNN or even DNN-based methods usually have limited ability to capture essential features from signal data. Factors like small-scale fading, noise, or NLOS effect can largely deteriorate the signal measurement and thus lead the location prediction away from the actual one. Adopting more advancing DL algorithms to increase efficiency the feature extraction is one of the directions to approach sub-meter level precision. Dou et al. [30] improves the precision by modeling the localization problem into a sequential searching process. The search space is getting narrowed down during the bisection process and eventually converge to the final location. Utilizing DRL-based algorithms enables the proposed method to update its location prediction accommodating any environmental changes or signal fluctuation during the searching process. The authors in [42] construct a structured MLP model with a unique loss function to overcome multi-path and fading effect to achieve sub-meter level accuracy in both indoor and outdoor environment. Besides, CNN [1,57,68] and autoencoder-based algorithms [46] are shown to be more powerful options comparing to traditional KNN or DNN-based approaches.

From the data point of view, CSI [46,48,57] or RTT-based [49] localization can potentially offer higher precision, because of the advantage in containing richer environmental information, and being more resilient to fading, multi-path effect, etc. For CSI data, developing feature engineering technique is another viable option to further enhance the localization performance [48]. Moreover, data or feature fusion in different signal metrics [15], channels or APs [43] or time-stamps [48] is also a potential design choice to enhance the robustness and resolve the problem when processing data in single modality.

6.2. Latency

For localization methods using DL-based algorithms, the time consumption consists of three categories: training time, run-time/test time, and data collection time. The run-time for localization methods attracts most of the interest of related studies, because it measures the time that a method needs to execute and output a location prediction, which is the one that mostly related to the time-efficiency of a localization application. In general, the algorithm or model complexity, data dimension, and data-preprocessing step can all be the source of run-time consumption. Early works like [12] achieves run time at 0.612 s in average with using CNN-based models to process RSS images. Hashem et al. [49] improve the location estimation time to 0.085 s while offering sub-meter level precision. The DNN-based methods proposed in [28] achieve the run-time consumption to around 0.01 s. The authors in [30] develop a bisection method to partition the space more efficiently to reduce the computation complexity. The time consumption can be reduced to 6–10 ms during the prediction stage for single-floor localization. In [3], the location prediction can be finished in around 5 ms while processing the image-type input data. A recent study in [41] achieves the run-time in as low as 31.1 µs maintaining the precision at around 1–2 m. In general, optimizing the run-time performance usually needs to sacrifice the localization accuracy or other performance metrics. Thus, how to determine the priority or to compensate the performance loss in either side should be taken into account as well.

Model training is the most time consuming part when considering the latency issue in DL-based methods. Large size-dataset and complex DL models or algorithms are usually effective in improving localization accuracy, but unavoidably extend the training time. Although the training process can be finished before deploying the service, which eases the needs of improving training efficiency in many cases, reducing the time spent on training DL model can still be necessary when there is demand of updating the model frequently with real-time signal measurements. Experiment and analysis on impact of the factors like size of LSTM units and batch size [57] or number of training samples [41] can be a good way to examine the optimal design choice for DL algorithms or determine the trade-off between the localization accuracy and time-efficiency or other concerns for a given application.

Besides, the time spent on collecting sufficient data to train or retrain the DL model is also a potential concern especially in real-time localization applications. Minimizing the data collection time can be achieved by reducing the number of data involved during the training process or the length of data samples for each received signal. If the DL model can be trained or retrained with less amount of data, it can be updated more frequently to accommodate any real-time environmental changes or signal fluctuation which impact the localization performance. Related analyses have already been conducted in [41,49] regarding training with few or even single RSS data sample. How to improve the data collection time efficiency while minimizing the localization precision still remains as a challenge.

6.3. Data Engineering

While implementing DL-based localization system, gathering sufficient and informative training data is usually a time and labor consuming process. This feature inevitably introduces excessive costs and leads to inefficiency in real-time deployment. Starting from the last few years, the Gen-AI model has been developed as a powerful image generation and data augmentation tool. The related algorithms and architectures soon become a promising solution to address the aforementioned data related issues in localization. GAN and variation auto-encoder (VAE) are two of the main generative architectures adopted in the related studies.

One of the major usage of Gen-AI models is to generate artificial signal data to satisfy the needs of training a DL-based localization model. In [94,95], the GAN-based algorithms are proposed to generate artificial CSI fingerprints to improve the localization accuracy. The GAN models implemented in [96,97] are utilized only to generate artificial RSSI data, but also to predict the corresponding coordinates to enrich the training dataset. The authors of [98] developed a GAN-based method to integrate the collected data and pre-defined ray-tracing signal propagation model to generate more realistic synthetic RSS maps.

Another common challenge in wireless localization application is that, some measured signal data are missed or polluted due to either the hardware malfunction or any moving objects blocking the signal propagation. This issue can potentially cause larger error in some trajectory or object tracking applications. Gen AI model is also considered to be a promising direction to approach this type of problem. In [99–101], the authors all implement a GAN-based model to recover the incomplete RSSI maps. A RNN model is further integrated in [99] to process the time-dependent information in order to serve for a tracking application. The GAN model proposed in [77] is trained not only to recover missed RSS samples, but also mitigating the effect of signal fluctuation, interference, and fading.

Gen AI models are also adopted to improve the data collection efficiency by reducing the amount of training data needed. In general, localization application requires a sufficient amount and evenly distributed sensors or reference points in the area to provide high precision and accurate location estimation. In [95], the authors aim at alleviating this data collection efforts by reducing the number of reference points needed in the data collection phase. They start with the data from a less amount and sparsely distributed reference points, and propose a GAN-based approach that can interpolate or estimate the CSI values for those intermediate reference points. In this way a dense radio map can be constructed by using the measurements from only a limited amount of reference points. Besides, Chen et al. [102] also consider using GAN model to explore how to generalize the spatial information collected from a small amount of labeled data to the set of unlabeled data, which can be collected any time during the actual localization service deployment stage.

Moreover, both GAN and VAE models are investigated to improve the localization accuracy. In [76], the GAN algorithm is implemented to improve both indoor and outdoor localization performance, and is able to achieve about 0.4 m-level of accuracy in indoor scenarios. The GAN-based method proposed in [103] can achieve 0.19 m-level of accuracy in the testing dataset while maintaining a very low model storage usage at about 50 Kb, which makes the localization service deployable at a mobile phone. In addition, the VAE is utilized as one of the most advancing and compelling feature extractor to process wireless signal data, and is adopted in [104] to exploit the distribution of RSSI data over the space.

6.4. Generality to Devices and Environments

While DL algorithms have been widely adopted in wireless localization, these types of learning-based methodologies can still be suffering when dealing with device and environment heterogeneity. Common DL-based localization works are implemented based-on a dataset collected using certain types of devices like cellphone, or in a particular environment such as a lab on campus. Although the DL models are trained and demonstrated to be effective on the given dataset, deploying the same models for locating a different hardware or in a new location while maintaining the same level of performance can be struggling, and thus become another major burden in the related fields. Another important reason that makes transferring the model challenging is that, common localization-related wireless data, including RSSI and CSI, can be heavily influenced by the device or environment variation, respectively. While containing the spatial information of a given environment or space, these data are too closely bonded with that some particular types of devices or a specific environment, which makes the models trained based on them lost the generality to other ones.

Therefore, recent studies also start to focus on how to relieve these impact by accommodating various DL-based designs or algorithms. In [105], the authors address the device heterogeneity issue by combing the ideas of transfer learning and multi-task learning. They showed that, by transferring the trained model on a base dataset and fine-tuning it with only a few RSS data samples from the new devices, the model can be adapted to locate the new devices as well. Hao et al. [106] proposed an adversarial training strategy to alleviate the variance introduced by the device heterogeneity. The studies in [107] focus on addressing the similar problem by designing a hybrid structure incorporating multiple formats of fingerprint and integrating multiple classifiers.

Regarding the cross-domain localization problem, the authors in [108] developed a semi-supervised learning framework and enabled the edge devices to work in a self-learning way to adopt environmental variations. The concept of meta-learning is studied and investigated in [109] to improve the model's adaptivity in a dynamic or unseen environment, while minimizing the efforts needed on retraining the model. Wang et al. investigated the idea of training the DL network to predict the AP-centered polar coordinate instead of the regular coordinates. In this way, the model can learn the relative spatial information rather than the absolute one, which improves the localization robustness against environmental variations. This work also adopted a multi-task learning frame work to enhance the accuracy. Zhang et al. [110] approaches the domain adaptation problem from another perspective: they introduced augmented CSI-based fingerprint into the learning framework, and implemented a forgetting mechanism to keep the model refreshing from outdated data. Their studies also demonstrate the real-time adaptivity to environmental changes. The authors in [111] build the foundation of their localization system in a fully self-supervised learning way. The model is forced to focused on the intrinsic information in the CSI fingerprint by training the model with unlabeled data. The experiment results show that this pre-trained model can work in a scenario-agnostic way by finetuning with very limited amount of data whenever it deployed to a different environment.

7. Conclusions

DL algorithms have been demonstrated to be effective in various localization scenarios. It is becoming an efficient way to process the wireless signal data and extract essential location information from it. Meanwhile, as a data-driven approach, DL-based localization method requires sufficient training data and effective data-preprocessing techniques to improve the feature extraction process. It is also crucial to consider different data format or modality, as well as proper algorithms for the particular localization applications. In this paper, we reviewed how the DL algorithms are adopted in different wireless environments to compensate the challenges in the corresponding localization tasks. Furthermore, we reviewed different components of a DL-based method, including the datasets, data preprocessing methods, DL algorithms, and simulators of localization scenarios, to support the future research and studies.

Author Contributions

H.X.: Conceptualization, methodology, data curation, investigation, writing—original draft; M.A.: conceptualization, methodology; A.C.: conceptualization, methodology; V.L.: conceptualization, methodology, funding acquisition; M.Z.W.: conceptualization, methodology, funding acquisition; Y.-D.Y.: conceptualization, methodology, writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Funding

This research was supported in part by the National Science Foundation under Grant CNS-2148251 and in part by federal agency and industry partners in the RINGS program.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Not applicable.

Conflicts of Interest

Given the role as Editor-in-Chief, Yu-Dong Yao had no involvement in the peer review of this paper and had no access to information regarding its peer-review process. Full responsibility for the editorial process of this paper was delegated to another editor of the journal. The authors declare no conflicts of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

References

1. Gao, K.; Wang, H.; Lv, H.; et al. Toward 5G NR high-precision indoor positioning via channel frequency response: A new paradigm and dataset generation method. *IEEE J. Sel. Areas Commun.* **2022**, *40*, 2233–2247.
2. Klus, R.; Klus, L.; Talvitie, J.; et al. Transfer learning for convolutional indoor positioning systems. In Proceedings of the International Conference on Indoor Positioning and Indoor Navigation (IPIN), Lloret de Mar, Spain, 29 November–2 December 2021.
3. Yapar, Ç.; Levie, R.; Kutyniok, G.; et al. Real-time outdoor localization using radio maps: A deep learning approach. *IEEE Trans. Wirel. Commun.* **2023**, *22*, 9703–9717.
4. Song, X.; Fan, X.; Xiang, C.; et al. A novel convolutional neural network based indoor localization framework with WiFi fingerprinting. *IEEE Access* **2019**, *7*, 110698–110709.
5. Wisanmongkol, J.; Taparugssanagorn, A.; Tran, L.C.; et al. An ensemble approach to deep-learning-based wireless indoor localization. *IET Wirel. Sens. Syst.* **2022**, *12*, 33–55.
6. Nikonowicz, J.; Mahmood, A.; Ashraf, M.I.; et al. Indoor positioning trends in 5G-advanced: Challenges and solution towards centimeter-level accuracy. *arXiv* **2022**, arXiv:2209.01183.
7. Dwivedi, S.; Shreevastav, R.; Munier, F.; et al. Positioning in 5G networks. *IEEE Commun. Mag.* **2021**, *59*, 38–44.
8. Mogyorósi, F.; Revisnyei, P.; Pašić, A.; et al. Positioning in 5G and 6G networks—A survey. *Sensors* **2022**, *22*, 4757.
9. Ayyalasomayajula, R.; Arun, A.; Wu, C.; et al. Deep learning based wireless localization for indoor navigation. In Proceedings of the 26th Annual International Conference on Mobile Computing and Networking, Virtual, 21–25 September 2020.
10. Ismail, M.I.M.; Dzyauddin, R.A.; Samsul, S.; et al. An RSSI-based wireless sensor node localisation using trilateration and multilateration methods for outdoor environment. *arXiv* **2019**, arXiv:1912.07801.
11. Tian, K.; Song, S.; Xu, W.; et al. Wireless Positioning Using Deep Learning with Data Augmentation Technique. In Proceedings of the IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Helsinki, Finland, 13–16 September 2021; pp. 1255–1259.
12. Chen, H.; Wang, B.; Pei, Y.; et al. A WiFi indoor localization method based on dilated CNN and support vector regression. In Proceedings of the Chinese Automation Congress (CAC), Shanghai, China, 6–8 November 2020; pp. 165–170.
13. Hoffmann, M.; Bogucka, H. Localization techniques for 5G radio environment maps. In Proceedings of the Cognitive Radio-Oriented Wireless Networks: 14th EAI International Conference, CrownCom 2019, Poznan, Poland, 11–12 June 2019; pp. 232–246.
14. Roy, P.; Chowdhury, C.; Ghosh, D.; et al. JUIndoorLoc: A ubiquitous framework for smartphone-based indoor localization subject to context and device heterogeneity. *Wirel. Pers. Commun.* **2019**, *106*, 739–762.
15. Lu, Y.M.; Sheu, J.P.; Kuo, Y.C. Deep learning for ultra-wideband indoor positioning. In Proceedings of the IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Helsinki, Finland, 13–16 September 2021; pp. 1260–1266.
16. Hoang, M.T.; Yuen, B.; Dong, X.; et al. Recurrent neural networks for accurate RSSI indoor localization. *IEEE Internet Things J.* **2019**, *6*, 10639–10651.
17. Sonny, A.; Kumar, A.; Cenkeramaddi, L.R. A survey of application of machine learning in wireless indoor positioning systems. *arXiv* **2024**, arXiv:2403.04333.
18. Burghal, D.; Ravi, A.T.; Rao, V.; et al. A comprehensive survey of machine learning based localization with wireless signals. *arXiv* **2020**, arXiv:2012.11171.

19. Roy, P.; Chowdhury, C. A survey of machine learning techniques for indoor localization and navigation systems. *J. Intell. Robot. Syst.* **2021**, *101*, 63.
20. Kordi, K.A.; Roslee, M.; Alias, M.Y.; et al. Survey of Indoor Localization Based on Deep Learning. *Comput. Mater. Contin.* **2024**, *79*, 3261.
21. Feng, X.; Nguyen, K.A.; Luo, Z. A survey of deep learning approaches for WiFi-based indoor positioning. *J. Inf. Telecommun.* **2022**, *6*, 163–216.
22. Nessa, A.; Adhikari, B.; Hussain, F.; et al. A survey of machine learning for indoor positioning. *IEEE Access* **2020**, *8*, 214945–214965.
23. Alhomayani, F.; Mahoor, M.H. Deep learning methods for fingerprint-based indoor positioning: A review. *J. Locat. Based Serv.* **2020**, *14*, 129–200.
24. Ye, Y.X.; Lu, A.N.; You, M.Y.; et al. Wireless localization based on deep learning: state of art and challenges. *Math. Probl. Eng.* **2020**, *2020*, 5214920.
25. Zafari, F.; Gkelias, A.; Leung, K.K. A survey of indoor localization systems and technologies. *IEEE Commun. Surv. Tutorials* **2019**, *21*, 2568–2599.
26. Roy, P.; Chowdhury, C.; Kundu, M.; et al. Novel weighted ensemble classifier for smartphone based indoor localization. *Expert Syst. Appl.* **2021**, *164*, 113758.
27. Torres-Sospedra, J.; Montoliu, R.; Martínez-Usó, A.; et al. UJIIndoorLoc: A new multi-building and multi-floor database for WLAN fingerprint-based indoor localization problems. In Proceedings of the International Conference on Indoor Positioning and Indoor Navigation (IPIN), Busan, Republic of Korea, 27–30 October 2014; pp. 261–270.
28. Wang, Y.; Gao, J.; Li, Z.; et al. Robust and accurate Wi-Fi fingerprint location recognition method based on deep neural network. *Appl. Sci.* **2020**, *10*, 321.
29. Sun, Q.; He, L.; Meng, F.; et al. Wireless communication indoor positioning method in 5G sub-station using deep neural network and location fingerprint algorithm. *Optik* **2022**, *271*, 170159.
30. Dou, F.; Lu, J.; Xu, T.; et al. A bisection reinforcement learning approach to 3-D indoor localization. *IEEE Internet Things J.* **2020**, *8*, 6519–6535.
31. Barsocchi, P.; Crivello, A.; La Rosa, D.; et al. A multisource and multivariate dataset for indoor localization methods based on WLAN and geo-magnetic field fingerprinting. In Proceedings of the International Conference on Indoor Positioning and Indoor Navigation (IPIN), Alcala de Henares, Spain, 4–7 October 2016.
32. Moreira, A.; Silva, I.; Torres-Sospedra, J. The DSI dataset for Wi-Fi fingerprinting using mobile devices. *Zenodo* **2020**. https://doi.org/10.5281/zenodo.3778646.
33. Mendoza-Silva, G.M.; Richter, P.; Torres-Sospedra, J.; et al. Long-term WiFi fingerprinting dataset for research on robust indoor positioning. *Data* **2018**, *3*, 3.
34. King, T.; Kopf, S.; Haenselmann, T.; et al. CRAWDAD dataset mannheim/compass (v. 2008-04-11). *Traceset Fingerprintc* **2008**. https://doi.org/10.15783/c7js3p.
35. Richter, P.; Lohan, E.S.; Talvitie, J. WLAN (WiFi) RSS database for fingerprinting positioning. *Zenodo* **2018**. https://doi.org/10.5281/zenodo.1161525.
36. Lohan, E. Additional TAU datasets for Wi-Fi fingerprinting-based positioning. *Zenodo* **2020**. https://doi.org/10.5281/zenodo.3819917.
37. Lohan, E.; Torres-Sospedra, J.; Richter, P.; et al. Crowdsourced WiFi-fingerprinting database and benchmark software for indoor positioning. *Zenodo* **2017**. https://doi.org/10.5281/zenodo.889798.
38. Alhomayani, F. Deep Learning Methods for Fingerprint-Based Indoor and Outdoor Positioning. Ph.D. Thesis, University of Denver, Denver, CO, USA, 2021.
39. Aranda, F.J.; Parralejo, F.; Álvarez, F.J.; et al. Multi-slot BLE raw database for accurate positioning in mixed indoor/outdoor environments. *Data* **2020**, *5*, 67.
40. Alhomayani, F.; Mahoor, M.H. OutFin, a multi-device and multi-modal dataset for outdoor localization based on the fingerprinting approach. *Sci. Data* **2021**, *8*, 66.
41. Nabati, M.; Ghorashi, S.A. A real-time fingerprint-based indoor positioning using deep learning and preceding states. *Expert Syst. Appl.* **2023**, *213*, 118889.
42. Comiter, M.Z.; Crouse, M.B.; Kung, H. A data-driven approach to localization for high frequency wireless mobile networks. In Proceedings of the GLOBECOM 2017-2017 IEEE Global Communications Conference, Singapore, 4–8 December 2017.
43. Koutris, A.; Siozos, T.; Kopsinis, Y.; et al. Deep Learning-Based Indoor Localization Using Multi-View BLE Signal. *Sensors* **2022**, *22*, 2759.
44. Zhang, Q.; Wang, Y. A 3D mobile positioning method based on deep learning for hospital applications. *Eurasip J. Wirel. Commun. Netw.* **2020**, *2020*, 170.
45. Liu, L.; Zhao, Q.; Miki, S.; et al. Indoor Fingerprinting Positioning System Using Deep Learning with Data Augmentation. *Sensors Mater.* **2022**, *34*, 3047–3061.
46. Wu, G.S.; Tseng, P.H. A deep neural network-based indoor positioning method using channel state information. In

Proceedings of the International Conference on Computing, Networking and Communications (ICNC), Maui, HI, USA, 5–8 March 2018; pp. 290–294.

47. Xiang, C.; Zhang, Z.; Zhang, S.; et al. Robust sub-meter level indoor localization-a logistic regression approach. In Proceedings of the ICC 2019-2019 IEEE International Conference on Communications (ICC), Shanghai, China, 20–24 May 2019.
48. Gönültaş, E.; Taner, S.; Huang, H.; et al. Feature Learning for Neural-Network-Based Positioning with Channel State Information. In Proceedings of the 55th Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, USA, 31 October–3 November 2021; pp. 156–161.
49. Hashem, O.; Harras, K.A.; Youssef, M. DeepNar: Robust time-based sub-meter indoor localization using deep learning. In Proceedings of the 17th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON), Como, Italy, 22–25 June 2020.
50. Torres-Sospedra, J.; Montoliu, R.; Trilles, S.; et al. Comprehensive analysis of distance and similarity measures for Wi-Fi fingerprinting indoor positioning systems. *Expert Syst. Appl.* **2015**, *42*, 9263–9278.
51. Jiang, M.; Yuan, J. A device free high-precision indoor positioning and tracking method based on GMM-WKNN algorithm. *Sci. Rep.* **2025**, *15*, 17586.
52. Guo, Y.; Yan, J. A CSI based localization and identification recognition algorithm using multi-task learning and deep residual shrinkage network. In Proceedings of the IEEE 22nd International Conference on Communication Technology (ICCT), Nanjing, China, 11–14 November 2022; pp. 1770–1776.
53. Zhang, Y.; Fan, M.; Xu, C. Intelligent indoor localization based on CSI via radio images and deep learning. *Meas. Sci. Technol.* **2023**, *34*, 085002.
54. Sobehy, A.; Renault, E.; Muhlethaler, P. NDR: Noise and dimensionality reduction of CSI for indoor positioning using deep learning. In Proceedings of the IEEE Global Communications Conference (GLOBECOM), Waikoloa, HI, USA, 9–13 December 2019.
55. Sobehy, A. Machine Learning Based Localization in 5G. Ph.D. Thesis, Institut Polytechnique de Paris, Palaiseau, France, 2020.
56. Poulose, A.; Han, D.S. UWB indoor localization using deep learning LSTM networks. *Appl. Sci.* **2020**, *10*, 6290.
57. Zhang, Z.; Lee, M.; Choi, S. Deep-learning-based Wi-Fi indoor positioning system using continuous CSI of trajectories. *Sensors* **2021**, *21*, 5776.
58. Jia, X.; Liu, P.; Qi, W.; et al. Link-level simulator for 5G localization. *IEEE Trans. Wirel. Commun.* **2023**, *22*, 5198–5213.
59. WinProp. ALTAIR Engineering Inc. Available online: https://web.altair.com/winprop-telecom (accessed on 18 July 2025).
60. Bluetooth LE Direction Finding for Tracking Node Position. Matlab Bluetooth Toolbox. Available online: https://www.mathworks.com/help/bluetooth/ug/bluetooth-le-node-tracking-using-direction-finding.html (accessed on 18 July 2025).
61. UWB Localization Using IEEE 802.15.4z. Matlab Communication Toolbox. Available online: https://www.mathworks.com/help/comm/ug/uwb-localization-using-ieee-802.15.4z.html (accessed on 18 July 2025).
62. Bluetooth LE Positioning by Using Direction Finding. Matlab Bluetooth Toolbox. Available online: https://www.mathworks.com/help/bluetooth/ug/bluetooth-le-based-positioning-using-direction-finding.html (accessed on 18 July 2025).
63. Time Difference of Arrival Positioning Using PRS. Matlab LTE Toolbox. Available online: https://www.mathworks.com/help/lte/ug/time-difference-of-arrival-positioning-using-prs.html (accessed on 18 July 2025).
64. 802.11az Positioning Using Super-Resolution Time of Arrival Estimation. Matlab Wi-Fi Toolbox. Available online: https://www.mathworks.com/help/wlan/ug/802-11az-indoor-positioning-using-super-resolution-time-of-arrival-estimation.html (accessed on 18 July 2025).
65. Communications Toolbox Library for ZigBee and UWB. Matlab Wi-Fi Toolbox. Available online: https://www.mathworks.com/matlabcentral/fileexchange/62845-communications-toolbox-library-for-zigbee-and-uwb?s_tid=srchtitle_5G%20localization_2 (accessed on 18 July 2025).
66. NR Positioning Using PRS. Matlab 5G Toolbox. Available online: https://www.mathworks.com/help/5g/ug/nr-prs-positioning.html (accessed on 18 July 2025).
67. Three-Dimensional Indoor Positioning with 802.11az Fingerprinting and Deep Learning. Matlab WLAN Toolbox. Available online: https://www.mathworks.com/help/wlan/ug/three-dimensional-indoor-positioning-with-802-11az-fingerprinting-and-deep-learning.html (accessed on 18 July 2025).
68. Xiang, C.; Zhang, S.; Xu, S.; et al. Robust sub-meter level indoor localization with a single WiFi access point—Regression versus classification. *IEEE Access* **2019**, *7*, 146309–146321.
69. Liu, K.; Tian, Z.; Li, Z.; et al. HiLoc: Sub-meter level indoor localization using a single access point with distributed antennas in wireless sensor networks. *IEEE Sensors J.* **2021**, *22*, 4869–4881.
70. Jog, S.; Guan, J.; Madani, S.; et al. Enabling IoT Self-Localization Using Ambient 5G Signals. In Proceedings of the 19th USENIX Symposium on Networked Systems Design and Implementation (NSDI 22), Renton, WA, USA, 4–6 April 2022; pp. 1011–1026.
71. Bartoletti, S.; Chiaraviglio, L.; Fortes, S.; et al. Location-based analytics in 5G and beyond. *IEEE Commun. Mag.* **2021**, *59*, 38–43.

72. Behravan, A.; Yajnanarayana, V.; Keskin, M.F.; et al. Positioning and sensing in 6G: Gaps, challenges, and opportunities. *IEEE Veh. Technol. Mag.* **2022**, *18*, 40–48.
73. Malmström, M.; Skog, I.; Razavi, S.M.; et al. 5G positioning-A machine learning approach. In Proceedings of the 16th Workshop on Positioning, Navigation and Communications (WPNC), Bremen, Germany, 23–24 October 2019.
74. Müürsepp, I.; Kulmar, M.; Elgarhy, O.; et al. Performance evaluation of 5G-NR positioning accuracy using time difference of arrival method. In Proceedings of the IEEE International Mediterranean Conference on Communications and Networking (MeditCom), Athens, Greece, 7–10 September 2021; pp. 494–499.
75. Arnold, M.; Hoydis, J.; ten Brink, S. Novel massive MIMO channel sounding data applied to deep learning-based indoor positioning. In Proceedings of the SCC 2019: 12th International ITG Conference on Systems, Communications and Coding, Rostock, Germany, 11–14 February 2019.
76. Serreli, L.; Nonnis, R.; Bingöl, G.; et al. Fingerprint-based positioning method over LTE advanced pro signals with GAN training contribute. In Proceedings of the IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB), Chengdu, China, 4–6 August 2021.
77. Tarekegn, G.B.; Juang, R.T.; Lin, H.P.; et al. Reduce fingerprint construction for positioning IoT devices based on generative adversarial nets. In Proceedings of the International Conference on Pervasive Artificial Intelligence (ICPAI), Taipei, Taiwan, 3–5 December 2020; pp. 23–28.
78. De Lima, C.; Belot, D.; Berkvens, R.; et al. Convergent communication, sensing and localization in 6G systems: An overview of technologies, opportunities and challenges. *IEEE Access* **2021**, *9*, 26902–26925.
79. Butt, M.M.; Rao, A.; Yoon, D. RF fingerprinting and deep learning assisted UE positioning in 5G. In Proceedings of the IEEE 91st Vehicular Technology Conference (VTC2020-Spring), Antwerp, Belgium, 25-28 May 2020.
80. Fan, S.; Wu, Y.; Han, C.; Wang, X. SIABR: A structured intra-attention bidirectional recurrent deep learning method for ultra-accurate terahertz indoor localization. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 2226–2240.
81. Fan, S.; Wu, Y.; Han, C.; et al. A structured bidirectional LSTM deep learning method for 3D terahertz indoor localization. In Proceedings of the IEEE INFOCOM 2020-IEEE Conference on Computer Communications, Toronto, ON, Canada, 6–9 July 2020; pp. 2381–2390.
82. Lei, H.; Zhang, J.; Xiao, H.; et al. Deep Learning Based Near-Field User Localization with Beam Squint in Wideband XL-MIMO Systems. *IEEE Trans. Wirel. Commun.* **2024**.
83. Ohtsuki, T. Machine learning in 6G wireless communications. *Ieice Trans. Commun.* **2023**, *106*, 75–83.
84. Alnoman, A.; Khwaja, A.S.; Anpalagan, A.; et al. Emerging AI and 6G-based user localization technologies for emergencies and disasters. *IEEE Access* **2024**, *12*, 197877–197906.
85. Zhang, J.; Xu, Z.; Zhang, S.; et al. A Deep Learning-Based Indoor Positioning Approach Using Channel and Spatial Attention. *IEEE Commun. Lett.* **2024**, *29*, 373–377.
86. Pan, G.; Huang, K.; Chen, H.; et al. Large Wireless Localization Model (LWLM): A Foundation Model for Positioning in 6G Networks. *arXiv* **2025**, arXiv:2505.10134.
87. Win, M.Z.; Meyer, F.; Liu, Z.; et al. Efficient multisensor localization for the Internet of Things: Exploring a new class of scalable localization algorithms. *IEEE Signal Process. Mag.* **2018**, *35*, 153–167.
88. Sadowski, S.; Spachos, P. RSSI-based indoor localization with the Internet of Things. *IEEE Access* **2018**, *6*, 30149–30161.
89. Bregar, K.; Mohorčič, M. Improving indoor localization using convolutional neural networks on computationally restricted devices. *IEEE Access* **2018**, *6*, 17429–17441.
90. Quezada-Gaibor, D.; Torres-Sospedra, J.; Nurmi, J.; et al. Surimi: Supervised radio map augmentation with deep learning and a generative adversarial network for fingerprint-based indoor positioning. In Proceedings of the IEEE 12th International Conference on Indoor Positioning and Indoor Navigation (IPIN), Beijing, China, 5–8 September 2022.
91. Wang, C.; Lin, Z. Precise indoor positioning based on UWB and deep learning. *arXiv* **2022**, arXiv:2204.07933.
92. Otim, T.; Bahillo, A.; Díez, L.E.; et al. Towards sub-meter level UWB indoor localization using body wearable sensors. *IEEE Access* **2020**, *8*, 178886–178899.
93. Säily, M.; Yilmaz, O.N.; Michalopoulos, D.S.; et al. Positioning technology trends and solutions toward 6G. In Proceedings of the IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Helsinki, Finland, 13–16 September 2021.
94. Wei, W.; Yan, J.; Wan, L.; et al. Enriching indoor localization fingerprint using a single AC-GAN. In Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC), Nanjing, China, 29 March–1 April 2021.
95. Lim, C.; Paek, J. Cost reduction in fingerprint-based indoor localization using generative adversarial network. In Proceedings of the International Conference on Information and Communication Technology Convergence (ICTC), Jeju Island, Republic of Korea, 20–22 October 2021; pp. 1024–1026.
96. Njima, W.; Chafii, M.; Shubair, R.M. GAN based data augmentation for indoor localization using labeled and unlabeled data. In Proceedings of the International Balkan Conference on Communications and Networking (BalkanCom), Novi Sad, Serbia, 20–22 September 2021; pp. 36–39.
97. Njima, W.; Chafii, M.; Chorti, A.; et al. Indoor localization using data augmentation via selective generative adversarial networks. *IEEE Access* **2021**, *9*, 98337–98347.

98. Zhou, M.; Lin, Y.; Zhao, N.; et al. Indoor WLAN intelligent target intrusion sensing using ray-aided generative adversarial network. *IEEE Trans. Emerg. Top. Comput. Intell.* **2020**, *4*, 61–73.
99. Belmonte-Hernandez, A.; Hernandez-Penaloza, G.; Gutiérrez, D.M.; et al. Recurrent model for wireless indoor tracking and positioning recovering using generative networks. *IEEE Sensors J.* **2019**, *20*, 3356–3365.
100. Njima, W.; Bazzi, A.; Chafii, M. DNN-based indoor localization under limited dataset using GANs and semi-supervised learning. *IEEE Access* **2022**, *10*, 69896–69909.
101. Ren, X.; Tao, W.; Own, C.M. RSS remeasurement estimation for indoor positioning system with generative adversarial network model. In Proceedings of the 2nd International Conference on Computing, Networks and Internet of Things, Beijing, China, 20–22 May 2021.
102. Chen, K.M.; Chang, R.Y. Semi-supervised learning with GANs for device-free fingerprinting indoor localization. In Proceedings of the GLOBECOM 2020-2020 IEEE Global Communications Conference, Taipei, Taiwan, 7–11 December 2020.
103. Liu, X.Y.; Wang, X. Real-time indoor localization for smartphones using tensor-generative adversarial nets. *IEEE Trans. Neural Netw. Learn. Syst.* **2020**, *32*, 3433–3443.
104. Suroso, D.J.; Cherntanomwong, P.; Sooraksa, P. Deep generative model-based RSSI synthesis for indoor localization. In Proceedings of the 19th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), Prachuap Khiri Khan, Thailand, 24-27 May 2022; pp. 1–5.
105. Shokry, A.; Youssef, M. Handling Device Heterogeneity for Deep Learning-based Localization. *arXiv* **2024**, arXiv:2407.16923.
106. Hao, L.; Huang, B.; Jia, B.; et al. DHCLoc: A device-heterogeneity-tolerant and channel-adaptive passive WiFi localization method based on DNN. *IEEE Internet Things J.* **2021**, *9*, 4863–4874.
107. Yuan, Y.; Liu, X.; Liu, Z.; et al. Indoor localization with wireless heterogeneous devices by composite fingerprint sets and hybrid classification. *IEEE Trans. Veh. Technol.* **2022**, *71*, 12117–12127.
108. Chen, P.; Zhang, K.; Gao, S.; et al. Achieving Cross-domain NLOS Localization via Edge-assisted Semi-supervised Learning. *IEEE Trans. Wirel. Commun.* **2025**, *24*, 7424–7436.
109. Owfi, A. Generalizable Deep-Learning-Based Wireless Indoor Localization. Master's Thesis, Clemson University, Clemson, SC, USA, 2023.
110. Zhang, J.; Xue, J.; Li, Y.; et al. Leveraging online learning for domain-adaptation in Wi-Fi-based device-free localization. *IEEE Trans. Mob. Comput.* **2025**, *24*, 7773–7787.
111. Zhang, L.; Qiu, Y.; Li, D.; et al. Scenario-Agnostic Deep-Learning-Based Localization with Contrastive Self-Supervised Pre-training. *arXiv* **2025**, arXiv:2508.03084.