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A Survey on Machine Learning Enhanced Integrated Sensing and Communication Systems: Architectures, Algorithms, and Applications

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ABSTRACT Integrated sensing and communications (ISAC) technology is being developed in wireless communications systems in the sixth generation (6G). ISAC has the advantages of lower cost, better spectral efficiency, and better energy efficiency than systems that use separate transceivers and receivers. This technology utilizes the same communication resources for communicating and sensing within the same framework, enabling more efficient use of resources. Currently, machine learning (ML) has been developed in the field of communications, including sensing and wireless communications, due to its ability to tackle complex optimization problems, estimate complex issues, and extract and exploit spatial/temporal patterns that can improve ISAC performance. This paper provides a comprehensive survey of ISAC systems enhanced by ML. We begin by presenting various system configurations based on the type of radar and target sensing and the sensing source utilized in the ISAC system, as well as real-world ISAC use cases. Following an overview of ML and deep learning (DL), we explore common types of ML and DL models and their potential to enhance ISAC systems. We review the application of ML in ISAC systems to enhanced sensing performance and optimize ISAC signals. Finally, we outline the potential avenues for future research aiming to improve ML application on ISAC systems and other prospective applications.

INDEX TERMS integrated signal and communication, machine learning, deep learning, localization, activity recognition, gesture recognition, channel estimation, waveform design, beamforming, signal processing.

I. INTRODUCTION

INTEGRATED sensing and communication (ISAC) is one of the technologies that is developed and has an important role in the sixth-generation (6G) wireless communication system [1]. ISAC is a system that combines wireless communication and radar sensing functions. ISAC has the advantages of higher energy efficiency, higher spectral efficiency, and lower costs compared to implementing separate communication and radar systems, each with its own dedicated devices. This is because each device requires a unique spectrum and transceiver to avoid interference. Having separate devices for communication and sensing results in higher energy consumption and greater spectral use than an integrated system. Furthermore, implementing separate systems requires purchasing additional devices, whereas ISAC allows communication devices to be used simultaneously for both communication and sensing. ISAC can provide sensing capabilities by leveraging existing communications infrastructure [2]. This can be achieved because the ISAC sensing and communication systems use the same hardware and frequency band [3]. These systems work simultaneously by sharing the same resources cooperatively, aiming to minimize interference from each other. Although the radar and communications systems may be physically integrated in the same location, they send different signals overlapping in the time or frequency domain [4]. Integration of communication and sensing can be achieved for the following reasons: First, radar and communication systems can be integrated because they share many similarities in hardware structure and system components. Second, the antenna structures of communication and radar systems are becoming more similar, as seen in multiple-input multiple-output (MIMO) systems and phased array radar. Third, communication bandwidth is expanding and even approaching the bandwidth of radar systems [5]. This technology can be used and applied in several areas, such as intelligent transportation [6], smart home [7], smart city [8], and various location-based services [9], [10].

Many researchers are developing 6G technology [11]. One of the main ideas behind creating 6G technology is to expand the utilization of artificial intelligence (AI) and machine learning (ML) in wireless networks for users. 6G will also provide advancements in several technical aspects, such as high throughput, supporting new applications with high demand, increased use of radio frequency bands, and more, using AI and ML techniques. ML has great capabilities for solving complex optimization problems, approximating intricate issues, and extracting and leveraging spatial/temporal patterns. With these advantages, ML has been developed in the fields of communication and sensing over the past few years [12]. As one of the technologies developed for 6G, ISAC can also leverage the advantages of ML to help improve sensing performance and optimize ISAC signals, for example, deep learning methods for integrated sensing and communication in vehicular networks [13], modified deep learning-based multi-input multi-output (MIMO) communication for integrated sensing, communication and computing systems [14], integrated sensing and communication-based breath monitoring using 5G network [15].

A. EXISTING SURVEY

In the past year, several studies have been on ISAC alongside ML or DL in 5G and 6G. D. K. Pin Tan *et al.* [16] explored ISAC design in 6G regarding four applications that can be supported by ISAC in the future, along with the key performance requirements for these applications. They also present the challenges of the designing of the ISAC system and outline future research directions for ISAC. In the future research directions section, the authors mention AI-enabled ISAC but do not elaborate in detail on real-world applications. A. Liu *et al.* [17] studies the limitations of current ISAC technology research, including state-of-the-art advancements and performance limits, aiming to provide insights and direction for the development of improved ISAC technology. Although they mention AI-aided ISAC but wasn't much discussed. J. Wang *et al.* [18] review ISAC from the perspective of the enabling techniques that can be

Acronym	Meaning
5G	Fifth-Generation
5G-A	Fifth-Generation Advance
6G	Sixth-Generation
AE	Autoencoders
AI	Artificial Intelliegence
ANN	Artificial Neural Network
ASL	American Sign Language
BS	Base Station
CNN	Convolution Neural Network
CSI	Channel State Information
DL	Deep Learning
DNN	Deep Neural Network
DoA	Degree of Arrival
DT	Decision Tree
EKF	Extended Kalman Filter
FFT	Fast Fourier Transform
FMCW	Frequency Modulated Continuous Wave
FPPA	Fast Parallel Proximal Algorithm
GMM	Gaussian Mixture Mode
GP	Gausian Process
GRU	Gates Recurrent Units
IoT	Internet of Things
IRS	Intelligent Reflecting Surface
ISAC	Integrated Sensing and Communication
KNN	K-Nearest Neighbor
LSTM	Long-Short Term Memory
MIMO	Multi Input Multi Output
ML	Machine Learning
NLP	Natural Language Processing
NN	Neural Network
OFDM	Orthogonal Frequency Division Multiplexing
PCA	Principal Component Analysis
RBF	Radial Basis Function
RF	Random Forest
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RSS	Received Signal Strength
SINR	Signal Interference Noise Ratio
SLAM	Simultaneous Localization and Mapping
SVM	Support Vector Machine
TCN	Temporal Convolution Network
THz	Terahertz
UAV	Unmanned Aerial Vehicles
UE	User Equipment
UWB	Ultra-wideband
WiFi	Wireless Fidelity

applied for ISAC, the applications for ISAC systems, and public datasets and tools that can be used for ISAC research. They mention ML for ISAC but not much is discussed.

U. Demirhan *et al.* [12] discusses the roles, reasons, and methods for implementing ML for integrated sensing and communication systems in joint sensing and communication, sensing-aided communication, and communication-aided sensing. While the potential of ML in ISAC is outlined, its implementation remains limited. S. Shao *et al.* [19] provide a survey of CSI-based sensing techniques, based on whether a custom physical model is built, or machine learning is used and their applications on detection, estimation, and recognition. However, they focus on ISAC related to CSI from Wi-Fi. These related papers have been summarized in Table 1.

B. OUR CONTRIBUTION

Our primary contributions to this survey are summarized as follows:

1) We provide an ISAC review based on various configurations and sensing sources used in ISAC systems as well as real-world ISAC applications to help improve communication performance and more.
2) We provide an overview of the basic principles in ML and DL and their potential applications in ISAC systems to improve performance and optimize ISAC signals.
3) We focus on ML-enhanced ISAC applications. We aim to explore how ML techniques can improve ISAC systems, boost their performance, and enable new features. We discuss specific use cases, real-world implementations, and potential future applications of ML in ISAC to give a complete understanding of how these technologies work together.

The organization of this paper is shown in Figure 1. In what follows, we give an overview of ISAC, including its system configuration, sensing source, and real-world applications in Section II. In Section III, we provide an overview of key concepts and techniques of ML. Section IV summarizes existing research on the application of ISAC with ML. Section V discusses potential future research to improve ISAC with ML. Finally, Section VI concludes this paper.

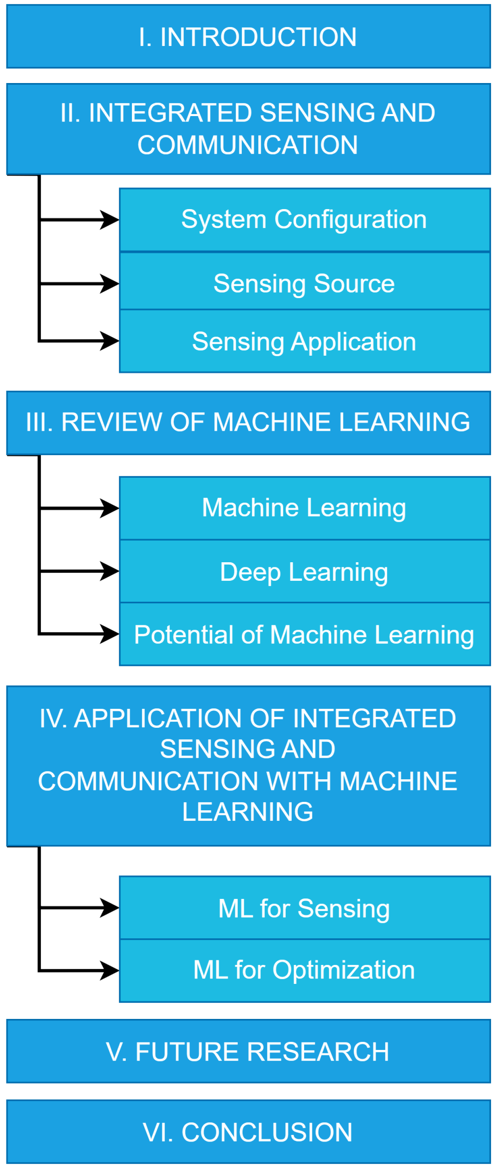

FIGURE 1: Overview of organization of this paper

II. INTEGRATED SENSING AND COMMUNICATION

Generally, sensing and communication functions work differently, so they need different resources like hardware, frequency band, and transmission schemes [25]. The main concept of ISAC is to improve resource efficiency for communications and sensing. With this concept, ISAC can use communication resources for sensing and communication, thereby improving system performance at a low cost [26]. Because no additional resources are required to perform sensing and communication separately, ISAC systems can reduce operational costs and investment in infrastructure.

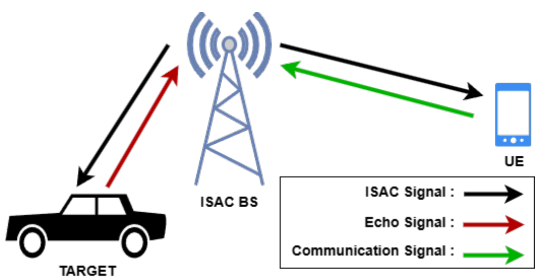

FIGURE 2: ISAC architecture

Figure 2 illustrates the ISAC architecture, which includes two key components for sensing using a communication

TABLE 1: List of Related Paper

Publication	Year	Summary	Limitation
[20]	2018	Explores the possible potential of AI-based solutions in 5G mobile and wireless communications technologies and evaluates various challenges and open issues for future research.	Discuss AI in 5G but ML-enhanced ISAC is not addressed.
[21]	2018	Surveys the application of DL algorithms in traffic balancing and different network layers, including physical, data link, and routing layers.	Discuss DL in a wireless network but ML-enhanced ISAC is not addressed.
[22]	2019	Discusses potential solutions from ML for 5G technology.	Discuss ML for 5G/B5G but ML-enhanced ISAC is not addressed.
[23]	2019	Comprehensive survey about the crossover between deep learning and mobile and wireless network research.	Discuss DL in mobile and wireless networks but ML-enhanced ISAC is not addressed.
[16]	2021	Discusses ISAC design in 6G regarding new applications, key performance, requirements, challenges, and future research directions.	Discuss ISAC use case in 6G, mentioning AI in future research section.
[11]	2021	Presents a demonstration of the utility and role of ML techniques and an up-to-date overview of future wireless system concepts.	Discuss ML for 5G and B5G but ML-enhanced ISAC is not addressed.
[17]	2022	Study the basic constraints of ISAC to understand the difference between today's state-of-the-art technology and its performance limitations.	Mentioning AI and ISAC in future research without delving into details.
[12]	2022	Focuses on the role of machine learning for integrated sensing and communications, explains how machine learning can be leveraged, and highlights important directions for future research.	Discuss ML for optimizing ISAC but there are still few real-world applications.
[18]	2022	Explores ISAC from the techniques, tools, applications, and data sets, as well as standardization, research challenges, and directions of future research.	Mentioning ML in ISAC in future research section but without delving into detail.
[24]	2022	Provides technological advances in the field of DL-based on physical layer methods for exciting 6G applications.	Discuss DL-aided 6G but ML-enhanced ISAC is not addressed.
[19]	2022	Provides a comprehensive survey of sensing techniques based on CSI, namely model-based, data-based, and hybrid-based methods combining models and data.	Discuss ML application in ISAC but focus on WLAN domain.

system: hardware and signal. The hardware component refers to the transmitter and receiver devices that send and receive communication and sensing signals. Common hardware configurations will be discussed in Section II.A. The signal transmitted by the transmitter toward the target will return to the receiver, and sensing information can be obtained by extracting information from the received signal. The source of sensing information will be discussed in Section II.B.

Integrating sensing and communication is challenging because sensing and communication have different information processing [27]. Communication focuses on transmitting information through designed signals and protecting them from noisy environments, while sensing focuses on obtaining information from noisy observations. The main object of ISAC is to combine these two processes and balance them, resulting in improved overall performance.

A. SYSTEM CONFIGURATION

ISAC works similarly to radar, so they have a similar configuration system. Radar types are classified based on transmitter and receiver locations into two categories: monostatic radar and bistatic radar.

- *Monostatic radars*: Monostatic radars is a radar system in which the transmitter and receiver are located at the same location.
- *Bistatic radars*: Bistatic radars is a radar system where the transmitter and receiver are positioned in different locations.

Conventional radar sensing can be classified based on target sensing into two categories: device-free and device-based.

- *Device-free*: Device-free sensing is a type of sensing where the target does not need or cannot use a device capable of receiving or transmitting radar signals. It's

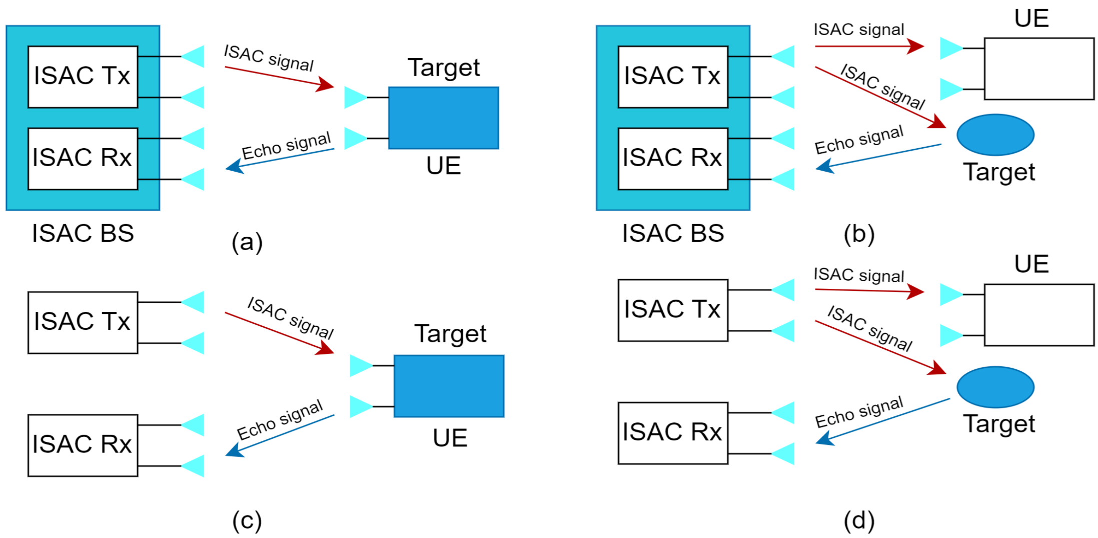

FIGURE 3: ISAC system configurations: (a) Case 1: Monostatic ISAC and device-based. (b) Case 2: Monostatic ISAC and device-free. (c) Case 3: Bistatic ISAC and device-based. (d) Case 4: Bistatic ISAC and device-free.

like traditional radar systems work, where targets are detected and localized based on reflection radar waves from targets [28].

- *Device-based*: Device-based sensing is a type of sensing where the target can receive and transmit both radar and communication signals. This category has more accurate localization compared to device-free because the targets can directly have access to reference signals and give the information to the radar [28].

From that category, ISAC system configurations can be categorized by four different cases [29] are illustrated in Fig.3. User Equipment (UE) can be an example of a device-based target radar because UE can receive from ISAC TX and transmit a signal to ISAC RX.

1) Case 1: Monostatic ISAC and device-based.

In Fig. 3(a), ISAC TX and RX are in the same ISAC BS as the target UE, which can send uplink signals to the ISAC BS. The uplink transmission process may affect the echo signal received by the RX. Additionally, self-interference from the TX can impact the performance of the RX. However monostatic ISAC has the advantage that because the RX uses the same clock and oscillator as the TX, it does not require frequency and time synchronization. In [30] considered self-interference as one of the problems in monostatic ISAC, therefore they proposed analog beamforming to suppress self-inference. Simulations show that the proposed method effectively solves the SINR maximization problem.

2) Case 2: Monostatic ISAC and device-free.

In Fig. 3(b), the target is not UE, so it can't interfere with the echo sensing signal to Radar Rx because it can't receive or transmit a signal, but it can be interrupted by self-interference on ISAC BS. ISAC TX signal can be used to sense the target and communicate with UE, so UE can get information about the target location on the second transmit after sensing the target. In [31] proposed a power allocation algorithm to minimize the maximum range estimation error at BS while considering total power and minimum signal-to-interference-noise ratio (SINR). This approach addresses the issue of localization accuracy in mono-static ISAC, which is challenged by inter-BS and self-interference at BS.

3) Case 3: Bistatic ISAC and device-based.

In Fig. 3(c), the target of the radar is UE, but ISAC TX and RX are placed with different antennae or towers, so it can minimize interference UE transmitting signal on echo sensing signal for ISAC RX and there is no self-interference between ISAC TX and RX. In [32], unmanned aerial vehicles (UAV) are used as a target device. The ISAC signal is transmitted using ISAC TX to the UAV, and the echo signal is received using a separate ISAC RX from ISAC TX. They proposed to optimize power allocation to the pilot and data parts in the communication structure for ISAC.

4) Case 4: Bistatic ISAC and device-free.

In Fig.3(d), the target is not UE, so it can't receive or transmit a signal, and ISAC TX and RX have been located in different antennae or towers. With this configuration, the advantages of bistatic ISAC and device-free operation are achieved, eliminating self-interference and interference from the target In [33] introducing bi-static orthogonal frequency-division multiplexing (OFDM) based for ISAC with over-the-air synchronization. In the testing stage, it uses a device-free target. In their conclusion, they state that several things influence the results of the experiment to be less good, but they also provide ways to overcome these problems.

B. SENSING SOURCE

In communication systems, channel or environment effect is compensated and estimated so the received signal can be decoded correctly; by using channel information on the received signal, sensing functions can be applied to detect targets and sensing parameter estimation [18]. With that concept, a combination of communication and sensing can be integrated into a communication system. In ISAC, the following typical forms for sensing are commonly used: Channel State Information (CSI), Receiver Signal Strength (RSS), and waveform directly.

1) Channel State Information

CSI is gained for each subcarrier in an OFDM system and is accessible on some commercial devices. CSI contains amplitude, phase, and frequency response, which are essential elements in wireless communication systems by revealing the intricacies of the communication channel between transmitter and receiver [34]. CSI data has been used for numerous sensing applications. In [35], the authors utilize CSI-based fire detection by leveraging CSI amplitude that correlates with fire. Meanwhile, in [36], the authors develop a framework for temperature sensing based on CSI amplitude. This is feasible because the kinetic energy present in ambient gas particles can affect the wireless link. In [37] utilized Wi-Fi CSI data for object detection. In [38] CSI and CNN for human activity recognition of Parkinson's disease patients. In [39] using CSI data to detect multivariety grain moisture.

2) Received Signal Strength

RSS is a physical layer measurement that reflects the propagation loss between transmitter and receiver, and it's commonly utilized in wireless systems. In general, signal propagation is assumed to follow an exponential decay path loss model, which is a function of the path loss factor, transmission-reception distance, and transmitted power [40]. RSS has been widely utilized for various sensing applications. In [41], RSS can be utilized to estimate crowd density with the K-means algorithm to clustering based on crowd density and get an accuracy of 94% for crowd static and 86% for crowd moving. In [42], RSS is used to locate a person by finding a person through their breathing. In [43], RSS is used for malicious UAV detection, and in [44] uses RSS for indoor localization.

3) Waveform

The principle of ISAC is similar to radar, so in addition to RSS and CSI, communication waveforms can also be used for sensing. Radar sensing utilizes frequency analysis over time and signal correlation to estimate Doppler frequency shift and delay, which can be interpreted as the distance and speed of a target. In using waveforms for sensing, waveforms can be specially designed to perform both communication and sensing. The waveform design is conducted in signal processing before modulation and then transmitted. Some examples of methods used to design waveforms include sparse vector coding-based for ISAC [45], generalized sparsely index modulation-OFDM for ISAC [46], and weighted-type fractional Fourier transform-based orthogonal time frequency space waveform design for ISAC [47]. There are two types of waveform commonly used for sensing: based on communication waveform and based on radar waveform. For the first type, there are several examples, like in [48] using WiFi signal for human sensing and in [49] using OFDM-based WiFi for passive sensing for moving targets. For the second type, in [50] using frequency-modulated continuous-wave (FMCW) for target detection. In [51] using FMCW for human sensing. In [52] using a waveform that transmitted from UAV to tracking object.in [53] using FMCW to make range detection.

C. SENSING APPLICATION

As one of the features in 6G, ISAC can improve communication performance by providing imaging, high-resolution sensing, localization, and environmental reconstruction [16]. This is achievable due to the use of higher frequency bands, such as mmWave up to THz, and wider bandwidth. This allows for more detailed sensing resolution, as higher frequencies use shorter wavelengths, and also improves accuracy due to the broader bandwidth. By utilizing communication systems as sensors, transmission, reflection, and scattering can be leveraged to sense and understand the physical world, enabling the development of new services. Additionally, this can also improve communication performance. There are four categories use case of ISAC as a service in 6G:

1) Precise Localization and Tracking

6G technology can be used to enhance precision in localization and tracking due to the use of high frequencies and wide bandwidth. Localization and tracking typically rely on Global Positioning System (GPS) technology, which works optimally for outdoor use but becomes challenging indoors as GPS signals are blocked by walls. In this case, ISAC can help improve accuracy in indoor environments, such as in [54] the author utilized an Extended Kalman Filter (EKF) with data from a BS transmitting sub-THz signals at a frequency of 142 GHz to track the UE. The experiment was conducted on a square track in both Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions, with 34 predetermined location points. As a result, the author achieved a mean position error of 24.8 cm. In addition to improving existing technologies, precise localization and tracking can also be used to enhance communication performance, such as optimizing beamforming to the UE accurately and quickly recovering from beam failure. It can also assist in indoor robot sensing and autonomous vehicles [55], reducing the need for additional hardware.

2) Simultaneous Localization and Mapping

Simultaneous Localization and Mapping (SLAM) is the ability to understand the surroundings (mapping) while determining location simultaneously. SLAM typically uses technologies like LiDAR or cameras (vision-SLAM), but these devices are expensive and consume a lot of power. ISAC presents an attractive solution for performing SLAM, as signals transmitted by the BS can be used. By leveraging the reflection or echo signals from walls or other objects received back at the BS, the environment can be mapped and the location of both the BS and other objects can be determined. M. Lotti *et al.* [56] proposed algorithm, Radio-SLAM (R-SLAM), is based on Fourier-Mellin (FM) transforms. FM is a technique used for image processing, and in this case, it is utilized to create a map of the surrounding environment and determine the location of devices based on the available data. The data used consists of THz backscattering. Three real-world experimental scenarios were conducted: the first with the radar directed toward the movement, then with the radar oriented perpendicular to the direction of movement, and the radar scanned the environment in 46 positions along an oval track characterized by diameters of 5 m and 3 m. In conclusion, the results of this experiment validate the feasibility of R-SLAM using backscattering signals in the THz band collected by a moving radar.

3) Enhanced Human Sensory Capabilities

Enhancing human sensory capabilities can help provide abilities that exceed human limits through portable terminals for sensing the surrounding environment. One scenario for utilizing ISAC is ISAC imaging, which can be achieved by leveraging the echoes from communication signals. As in [57] by utilizing THz, which has short wavelengths and high imaging resolution, terminal imaging using OFDM communication in the THz band can be used to obtain high-resolution images. However, achieving this comes with a high time cost. To address this, the author employs compressed sensing (CS) to reconstruct images using under-sampled echo data from OFDM-THz, allowing for faster data collection while still producing high-resolution images. Simulation and experimental results show that the proposed method outperforms the Fast Parallel Proximal Algorithm (FPPA) [58].

ISAC can also be used to detect objects behind walls, which are invisible to the human eye, enhancing human sensory capabilities. For instance, [59] discusses the fundamental radio technology used in see-through-wall systems. In [60], a method for 3D imaging is implemented using delay-and-sum beamforming, while [61] designs an UWB radar system for detecting and locating targets behind walls.

4) Recognition of Gestures and Activities

The high sensing resolution from utilizing high-frequency waves can be used to better capture human movements or activities. By leveraging high-accuracy gesture recognition, this can be implemented for use in human-computer interaction. As in [62]many gesture recognition systems are affected by background noise. To address this issue, the author proposed a multimodal fusion-Gaussian Mixture Model (GMM) for gesture recognition by utilizing CSI data. The multimodal approach involves using both sensing and recognition models, which are then combined using GMM. The sensing model is used to understand the impact of gestures on WiFi signal CSI, while the recognition model detects changes in the signal influenced by the gesture. Experiments were conducted in a laboratory and a corridor, yielding an average accuracy of 96% and 94%, respectively.

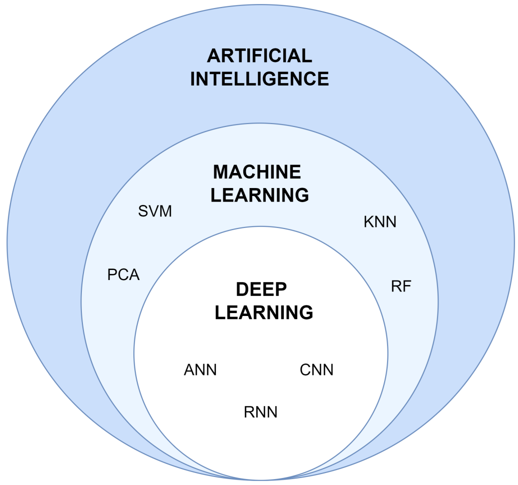

FIGURE 4: Illustration of the relationship between AI, ML, and DL

III. REVIEW OF MACHINE LEARNING

In this section, we discuss machine learning, deep learning, and the potential of machine learning on ISAC. Machine learning is a program of computers that is given to complete a task based on learning from the experience gained by the machine. Performance on these tasks improves with increased practice in solving them over time [63], meaning the machine solves the problem and makes its decisions based on the historical data it has learned. In the context of artificial intelligence, machine learning is the ability of machines to adapt without human influence, and deep learning is a subset of machine learning inspired by human neural networks that simulate the learning procedures of the human brain.

A. MACHINE LEARNING

Machine learning is a field of study that provides computers with capabilities that can allow them to learn without being explicitly programmed [64]. With that ability, computers can make predictions, classifications, or decisions without depending on hard-coded rules. ML is a development of the field of pattern recognition and artificial intelligence, which is a subfield of computer science [65] illustrated in Figure 4. Based on data availability and the problems encountered, there are three general categories of learning types: supervised learning, unsupervised learning, and reinforcement

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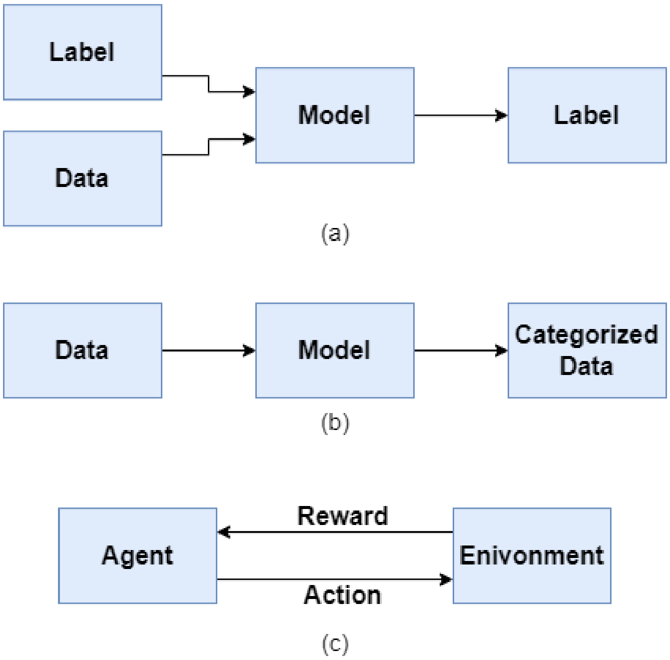

FIGURE 5: Illustration of (a) Supervised learning, (b) Unsupervised learning, and (c) Reinforcement learning.

learning [66], [67].

1) Supervised

Supervised learning is a learning method that uses a dataset containing examples and their labeled target [68], illustrated in Fig.5(a). Based on the output, supervised learning can be grouped into two categories: regression for the numerical output and classification for categorical output [69]. Some supervised learning algorithms usually used, such as support vector machine (SVM), K-nearest neighbor (KNN), random forest (RF), decision tree (DT), neural network (NN), hidden Markov model, and Bayes theory [70].

2) Unsupervised

Unsupervised learning is a learning method that uses a dataset containing only the example without the targets, so the model learns the property of the dataset. The goal of unsupervised learning is finding relations and patterns between data in dataset [64], illustrated in Fig.5(b). Unsupervised learning is a powerful tool for anomaly detection from finding relations or patterns between data so that it can identify unusual patterns in the dataset. Besides that, unsupervised learning can be used for dimensionality reduction. There are two popular dimensionality reduction methods: Autoencoders(AE) and Principal Component Analysis (PCA) [71].

3) Reinforcement Learning

Reinforcement learning is a learning method that utilizes an agent to make decisions by taking actions that yield positive rewards [64]. Agents learn from performing actions in the environment, and each action causes changes in the environment and produces rewards, which can be positive or negative. Rewards will be generated from actions performed in an episode. Episodes represent a finite number of actions and will end when the agent reaches the final state. The agent's goal is to maximize the positive value of the expected reward amount, which will encourage the agent to choose an action [72], illustrated in Fig.5(c). There are several algorithms that are used in reinforcement learning, for example, Q-learning [73], Markov decision processes (MDP) [74], and deep Q-network [75].

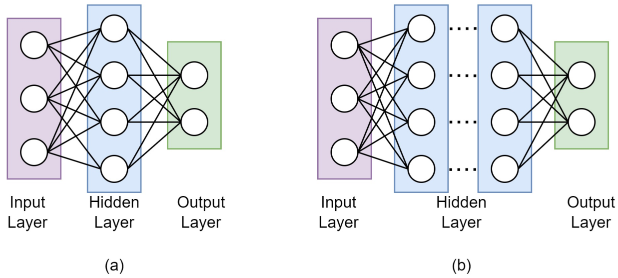

FIGURE 6: (a) Neural Network. (b) Deep Neural Network

B. DEEP LEARNING

Deep learning is a subset of machine learning, so it basically has the same purpose as making predictions, classifications, or decisions based on input data without explicitly programming [23]. Deep learning has neural networks as its basis, but DL focuses on learning deeper representations [76], [77]. It is because deep learning commonly uses more than one hidden layer, illustrated in Figure 6. Neural networks consist of three layers: input, hidden, and output layer. The input layer is the layer used to enter data into the neural network, and this part will determine the dimensions of the data that will be used as input. The hidden layer is the layer that handles the learning process from the data provided by the input layer. The output layer is the layer that produces the final output of the neural network. Three standard deep learning models are used: artificial neural network (ANN), convolution neural network (CNN), and recurrent neural network (RNN).

1) Artificial Neural Network (ANN)

ANN is inspired by the neural network in the human body. There are nodes connected to other nodes that can process input and forward output to other nodes in the network. ANN consists of three or more interconnected layers. ANN has another name: feed-forward neural network, because the input processing is unidirectional [78]. ANN has the same structure as a neural network. The first layer is the input layer that receives data, the layer between the input and output layers is the hidden layer, and the last layer is the output layer that provides output [79], illustrated in Figure 7(a). There are several ANN applications, in [80] using ANN to classify faults on wireless mesh networks, in [81] ANN-based localization in wireless sensor network, and not only

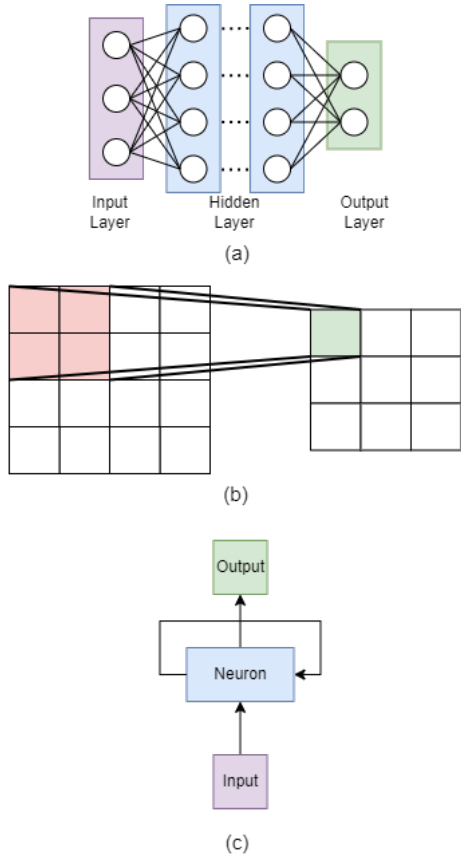

FIGURE 7: Illustration of (a) ANN, (b) CNN, and (c) RNN.

for a wireless domain, in [82] make model ANN-based for estimating state-of-charge lithium-ion batteries, and in [83] a complex neural network is used to estimate the Angle of Departure (AoD) from the communication signal and the Angle of Arrival (AoA) from the echo signal of the target. This NN-based method achieves good results with lower computational complexity compared to benchmark methods.

2) Convolution Neural Network (CNN)

CNN uses convolution operations in mathematics and signal processing in the node of a neural network, illustrated in Figure 7(b). Usually, CNN is used in image and video data because CNN can be used to identify features in images, such as edges. CNN commonly combines with the pooling layer to reduce the dimension of data [84], [85]. CNN has three main layers. The convolutional layer is used for feature extraction by applying convolutional operations to capture essential information from input data. The pooling layer for reducing complexity and number of features. The fully connected layer for the classification task, mapping the extracted feature to specific class [86]. Usually, CNN is used in image and video data because CNN can be used to identify features in images, such as edges. For example, CNN handles image and video data in [87] using CNN for breast cancer image retrieval, in [88] proposed CNN-based for video copyright detection, and [89] proposes fake 3D video detection based on CNN. CNN can also be applied in communication technology. For example, in [90], a CNN is used for wireless channel recognition, enabling the model to identify channel states efficiently. Additionally, [91] demonstrates the use of CNN to assess indoor wireless environment conditions, providing insights into environmental factors affecting wireless communication.

3) Recurrent Neural Network (RNN)

Neural networks have weaknesses in learning time series data because nodes can store information from previous nodes. To overcome this problem, RNN can be a solution because RNN stores information from previous nodes to learn time series data [85], illustrated in Figure 7(c). RNN has some issues with the application, such as vanishing gradients and exploded gradients. A vanishing gradient occurs when gradient updates are too small during training, which will affect the network learning process. Exploded gradient occurs when the cumulative gradient during the backpropagation process updates is too large for the network. To overcome this issue, there are various types of RNN called Gates Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) [92]. The Example RNN handles time series data in [93] using LSTM to make a prediction of a number of restaurant customers, in [94] forecasting COVID-19 confirmed case with LSTM-based, and in [95] proposed RNN for forecasting the computer network traffic.

C. POTENTIAL OF MACHINE LEARNING

Machine learning has been utilized in wireless communication technology, both in 5G and 6G. ML can be used to solve existing problems [20], [22] and optimize wireless networks [11], [21], [23], [96]. ISAC, which is one of the technologies developed for 6G networks, can also take advantage of ML to support ISAC sensing capabilities and optimize ISAC signals. With ML ability to learn from data, it can be used to improve sensing services [16]. Radio frequency performance is also based on the data processing and detection algorithms used. Learning-based detection algorithms can increase computational speed because ML can utilize parallel computing.

In addition to faster computation, ML can also help solve complex calculations that cannot be handled by traditional mathematics [17]. With the large amount of data and the complexity of ISAC applications, particularly in indoor environments [97], there are numerous disturbances and non-linear signals in the system that may be unknown or difficult to model. ML's ability to transform collected data into insightful knowledge can help make decisions and achieve automation [18].

ML can handle complex calculations and data by using tensor-based algorithms, which allow it to address high-dimensional data challenges. Tensor-based methods achieve this by performing tensor decomposition, which transforms high-dimensional tensors into sparse factor matrices and low-order core tensors [98]. By reducing data dimensionality, calculations can be processed faster. A major advantage of tensor decomposition is that it preserves data structure and

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correlations, meaning that decomposed data still represents the original information accurately, leading to faster and more accurate results.

In addition to ML, tensor decomposition is also applicable in signal processing [99]. Studies such as [100]–[103] use tensor decomposition for channel estimation in MIMO systems, while [104] applies it to estimate both channel and target location.

With all its advantages, ML is not suitable for every problem. There are certain conditions for the application of ML, including the problem type, dataset quality, time cost, and implementation complexity [105].

- *Problem Type*: Problems commonly addressed by ML can be categorized into regression, classification, and decision-making tasks. If the problem falls within these categories, then ML is often a suitable solution.
- *Dataset Quality*: To produce a reliable ML model, a high-quality dataset is essential. A good dataset is large and diverse enough to handle a variety of situations, enabling the model to generalize well. If such a dataset is available, ML can be applied effectively.
- *Time Cost*: Time cost includes both training time (the time required for model training) and response time (the time required for the model to produce an output). If the trained model has acceptable training and, especially, response times, ML is a feasible choice.
- *Implementation Complexity*: Consider whether implementing an ML model adds excessive complexity or if it improves system performance. ML should be used if it significantly enhances the system's efficiency.

IV. APPLICATION OF INTEGRATED SENSING AND COMMUNICATION WITH MACHINE LEARNING

This section will discuss the applications of ISAC with ML in two main categories: ML for sensing and ML for optimizing ISAC.

A. ML FOR SENSING

ML for sensing utilizes ML to improve ISAC sensing performance. This paper surveyed four main categories based on the use case mentioned on section II: localization, activity recognition, gesture recognition, and others. These sections have been summarized in Table 2.

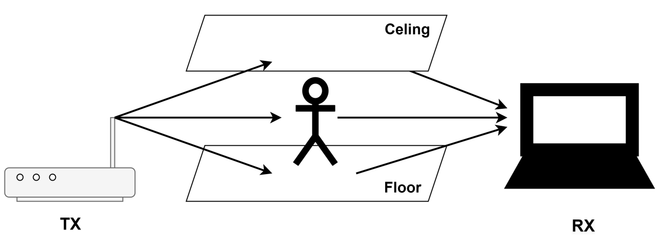

FIGURE 8: Illustration of indoor WiFi sensing

1) Localization

Localization aims to track and locate targets. Localization can be divided into two: outdoor and indoor [118]. This section will focus on indoor localization. Indoor localization is tracking and locating targets in indoor areas where the global positioning system can't work effectively. There are various technologies, such as wireless signals like WiFi, Bluetooth, ultra-wideband, optical systems like cameras, and LiDAR. Indoor localization using WiFi is illustrated in Figure 8.

L. Zhang *et al.* [106] using ML-based integrated indoor/outdoor sensing and positioning for cellular networks. Based on the authors' knowledge, this is one of the first integrated studies of radio frequency communication signals for cellular network operation in indoor/outdoor sensing and positioning. First, measurement reports are collected from layer 3 on the evolved NodeBs and indoor and outdoor user equipment across urban areas to emulate the minimization of driving tests. Then, the mobile scenarios are sensed, and the database is preprocessed to filter the positioning fingerprint using a random forest-based indoor/outdoor classifier. After that, weighted K-nearest neighbor-based Enhanced Cell ID is employed for radio frequency fingerprinting positioning. The proposed method of database preprocessing using indoor/outdoor classifiers achieves an accuracy of up to 97%, demonstrating its effectiveness in filtering fingerprints for radio frequency fingerprint positioning by comparing positioning errors.

Z. Zhang *et al.* [107] proposed transformer-based for indoor positioning. Utilize the CSI and estimate the degree of arrival (DoA) from Wi-Fi signal transmitter, that data will be preprocessed and fed to the transformer model. The transformer will be learning the correlation between the fingerprint and positions. With an attention mechanism in the transformer, so transformer can predict the current position using input data and the previous position, which can boost the accuracy. Transformer was introduced for natural language processing (NLP) [119]. The transformer has both an encoder and a decoder, but the author only uses the encoder part, similar to a Generative Pre-trained Transformer (GPT). GPT can predict the word at the current step based on the words generated at the previous time step. Then, the word at the next time step is generated based on the current and previous time steps. In this way, GPT produces output predictions sequentially. The author believes that using the transformer to predict positions, in the same manner as GPT, is an appropriate approach. The results using the method that was approached obtained an error distance accuracy of 20 cm.

Y. Dong *et al.* [108] leveraging LSTM for indoor positioning based on RSS. While LSTM has the potential to utilize temporal memory, RSS has high-dimensional data, which can reduce training performance and lower positioning accuracy. The author proposed an encoded LSTM consisting of two modules: an encoder and a predictor. The encoder is used to extract features and reduce the dimensionality of the input data, while the predictor is used to predict the location based

TABLE 2: List of Applications ML For Sensing

Application	Research	Title	Year	Dataset	ML Type
Localization	[106]	Machine learning-based integrated wireless sensing and positioning for cellular network	2023	cellular network	KNN-ECID
	[107]	TIPS: Transformer Based Indoor Positioning System Using Both CSI and DoA of Wi-Fi Signal	2022	Wi-Fi CSI	Transformer
	[108]	An Encoded LSTM Network Model for Wi-Fi-based Indoor Positioning	2022	RSS	LSTM
	[109]	DNN-Based Indoor Localization Under Limited Dataset Using GANs and Semi-Supervised Learning	2022	RSS	DNN
Activity Recognition	[110]	An Integrated Sensing and Communication System for Fall Detection and Recognition Using Ultra-wideband Signals	2024	UWB	1-D CNN
	[111]	Wi-Monitor: Daily Activity Monitoring Using Commodity Wi-Fi	2023	Wi-Fi CSI	TCN
	[112]	5G-Based Passive Radar Sensing for Human Activity Recognition Using Deep Learning	2024	5G CSI	LeNet-5 (CNN)
Gesture Recognition	[113]	Monitoring Respiratory Motion With Wi-Fi CSI: Characterizing Performance and the BreatheSmart Algorithm	2022	Wi-Fi CSI	LSTM
	[114]	Wi-Fi CSI Based Human Sign Language Recognition using LSTM Network	2021	Wi-Fi CSI	LSTM
	[115]	Position and Orientation Independent Wireless Gesture Recognition	2022	Wi-Fi CSI	CNN
Other Applications	[116]	Feasibility of Wind Speed Detection Using WiFi Sensing to Enable Unconventional IoT Applications	2024	Wi-Fi CSI	SVM
	[117]	Humidity Estimation Using WiFi Channel State Information	2023	Wi-Fi CSI	GP

on the extracted features. Based on experimental results, the proposed method shows a 10% improvement in accuracy compared to previous methods using the same dataset.

W. Njima *et al.* [109] using DNN for indoor localization involves using RSS as input data, which is limited in quantity. To overcome the data quantity limitations, the authors use a Generative Adversarial Network (GAN) to reproduce a fake dataset based on the existing dataset. In several testing scenarios, the accuracy of the model generated using the combined dataset from GAN and the original dataset showed improvement compared to the model using only the original dataset.

2) Gesture Recognition

Gesture recognition is the process of a system becoming aware of gestures provided by a user [120]. There are two essential components in gesture recognition: gesture reading and identification. Gesture reading retrieves data and information from sensors when the user performs a gesture. Gesture identification then interprets the gestures made by the user using a mathematical approach.

S. Mosleh *et al.* [113] proposed BreatheSmart system detects human respiration motions using Wi-Fi CSI that employs a bidirectional LSTM. Data is generated by capturing CSI Wi-Fi data streams for each pattern or speed of respiratory movement with a frame rate of 10 for 60 seconds. Several preprocessing steps are applied before feeding the data into the deep neural network. These steps are to identify respiratory frequencies from the power spectrum, learn and extract respiratory features from CSI, and normalize the data to aid model training using low pass filters, Hampel filters, and Fast Fourier Transform (FFT). The bidirectional-LSTM model is designed to learn from time-series data, passing information to subsequent layers to produce the classification of respiratory patterns and rates. The model's performance is evaluated using several metrics: precision, accuracy, specificity, recall, and F1-score. The model achieves impressive results, with a precision of 99.58%, accuracy of 99.54%, specificity of 99.94%, recall of 99.56%, and an F1-score of 99.57%.

H. F. Thariq Ahmed *et al.* [114] using LSTM for human sign language recognition with Wi-Fi CSI data. The dataset is from an open source dataset from SignFi that contains the American Sign Language (ASL) CSI dataset from home and lab; with the single-user scenario, 8,280 samples were acquired for 276 ASL gestures. CSI dataset consists of amplitude and phase data. There are several test conditions in this experiment; there is a variation on a dataset that used (amplitude only and amplitude + phase), environments (home and lab) optimizers (SDGM and Adam), and hidden units on LSTM (50, 100, and 150). From the experiment, the best performance was LSTM with 150 hidden units and Adam optimizer using an amplitude-only dataset. With this combination, the lab 276 dataset gets 99.8%, the home 276 dataset gets 99.5%, the lab+home 276 dataset gets 99.4%, and the lab 150 dataset gets 78.0% accuracy points.

Y. Wang *et al.* [115] proposed position and orientation independent wireless gesture recognition. Utilizing CNN to recognize six different gestures, this method is used to acknowledge the trajectory of every gesture. In this experiment, data used for training was generated by simulation; it generated 9000 trajectory data and for the testing data using CSI data obtained from a real receiver. For the actual testing data, the dataset is collected from two position configurations that were not present in the training data and training stage to verify the model performance. In the testing stage, there are 5 times tests; the result is for the first position to obtain 96% for average accuracy and the second position to obtain 85.7% for average accuracy.

3) Activity Recognition

Activity recognition is the ability to use sensors to sense and interpret human body signals or movements and determine human activity or actions [121]. Different from gesture or action recognition, activity recognition not only focuses on the movement part of the body but also includes the body's movement, such as posture, gait, sitting, leg posture, etc [122].

Li *et al.* [110] presenting FallDR using ultra-wideband communication for fall detection and recognition. Four DWM1000 modules are used for hardware testing: three as base stations (BS A, BS B, BS C) and one as a receiver. This experiment involved ten volunteers: two women and eight men. There are four types of falls: fall backward, fall forward, fall right, and fall left, and each action is performed 50-100 times. Additionally, they measured other activities like "kneeling," "walking," and "sitting down" to be "non-fall" data. There are 4047 sample data: 1000 samples representing "fall backward," 961 samples representing "fall backward," 836 samples representing "fall left," 690 samples representing "fall right," and 560 samples representing "non-fall." The proposed method that utilizes a 1-Dimensional CNN (1-D CNN) with the baseline methods is support vector machine-radial basis function (SVM-RBF), random forest (RF), and K-nearest neighbor (KNN). The first stage of this experiment is fall detection and then fall recognition. For fall detection, several metrics evaluations, such as accuracy, precision, specificity, sensitivity, and F-1 score, are used; for fall recognition, accuracy is used. The proposed method outperformed the baseline method with 100% accuracy, precision, specificity, sensitivity, and F-1 score for fall detection and 100% accuracy for fall recognition. This method's robustness is demonstrated by consistently outperforming baseline methods even with different environments.

Zhou *et al.* [111] introduce Wi-Monitor to monitor human activities using Wi-Fi CSI. The CSI data is collected and fragmented into CSI bins. Then, features are extracted from the bins using a feature extraction network that is composed of several residual convolution networks and a fully connected layer. After that, the temporal convolutional network (TCN) captures continuous activity patterns across three scenarios: basic, cross-subject, and cross-environment. TCN performance is compared to other methods, such as LSTM and over-segmentation suppression mechanism (OSSM); TCN demonstrates superior results all across scenarios. TCN achieves an average 96% f1-score and 93% accuracy in basic scenario, 93% f1-score and 92% accuracy in cross-subject scenario, and 90% f1-score and 92% accuracy in cross-environment scenario.

M. Dwivedi *et al.* [112] utilize 5G new radio for passive radar and activity recognition. The proposal is leveraging the synchronization signal block (SSB) to get CSI from extracting the SSB using secondary synchronization signal (SSS) and physical broadcast channel demodulation reference signal (PBCH DM-RS), then fed into modified LeNet-5 [123] based on CNN to classify the activity. Modified LeNet-5 is chosen because have fewer parameters than the other typical model [124]. There are 5 categories: wave, run, pickup, clap, and no activity. With the proposed method, it gets a training accuracy of 97.73% and a validation accuracy of 98.48%.

4) Other Applications

There are other applications of ISAC with ML for sensing objects other than humans.

Y. Deng *et al.* [116] utilizes WiFi sensing to detect wind speed, offering potential applications for unconventional IoT in smart cities. In this experiment, aluminum foil slices have good reflectivity of electromagnetic waves, which could amplify the perturbation to CSI and thus increase the sensitivity to obstacle movements. They propose a framework using the movement of obstacles within the WiFi channel to create unique CSI, which can be classified using SVM. There are 4 conditions with a different number of obstacles, 0 to 4 aluminum foil slices and 4-speed classes, 0.0m/s, 0.8m/s, 1.3m/s, and 1.8m/s. They achieve more than 90% accuracy in predicting 4 wind classes.

M. Burke *et al.* [117] Proposed humidity estimation using Wi-Fi CSI. This idea utilizes GP regression for estimating the humidity. Before being fed to GP, CSI data will be preprocessed using a Hampel filter to filter noisy data. The CSI data is using nearly 13 Million data consisting of 440 humidity data with each humidity data having 600 CSI every 48 subcarriers. From the experiment, the proposed method had a R^2 value of 0.92 and an average mean absolute percentage error of 93%.

TABLE 3: List of Applications ML For Optimization

Application	Research	Title	Year	Dataset	ML Type
Channel Estimation	[125]	Deep-Learning-Based Channel Estimation for IRS-Assisted ISAC System	2022	Channel	DNN
	[126]	Joint Target Sensing and Channel Estimation for IRS-Aided mmWave ISAC Systems	2024	ISAC signal	TVBI
	[127]	Extreme Learning Machine-Based Channel Estimation in IRS-Assisted Multi-User ISAC System	2023	ISAC signal	NN
	[128]	Deep-Learning Channel Estimation for IRS-Assisted Integrated Sensing and Communication System	2022	ISAC signal	CNN
Waveform or Beamforming Design	[129]	DL-based Joint Waveform and Beamforming Design for Integrated Sensing and Communication	2023	ISAC signal	FCNN
	[130]	Deep Learning-based Design of Uplink Integrated Sensing and Communication	2024	ISAC signal	CNN
	[131]	A Deep Reinforcement Learning Approach for Integrated Automotive Radar Sensing and Communication	2022	ISAC signal	DQN
Signal Processing	[13]	Deep-learning methods for integrated sensing and communication in vehicular networks	2023	ISAC signal	DNN & CNN
	[132]	ISAC-NET: Model-driven Deep Learning for Integrated Passive Sensing and Communication	2024	ISAC signal	NN
	[133]	Sensing Integrated DFT-Spread OFDM Waveform and Deep Learning-Powered Receiver Design for Terahertz Integrated Sensing and Communication Systems	2022	ISAC signal	NN

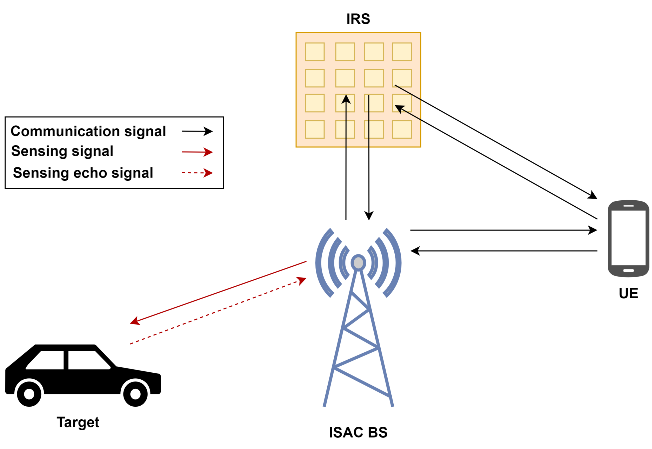

FIGURE 9: System model IRS-aided ISAC

B. ML FOR OPTIMIZATION

ML for optimization utilizes ML to optimize the quality and processing of ISAC signal. There are 3 categories surveyed in this paper: channel estimation, waveform or beamforming design, and signal processing. These sections have been summarized in Table 3.

1) Channel Estimation

Channel estimation techniques are usually required in wireless communications to ensure that the receiver can receive the generated information without distortion [134]. Channel estimation is used in determining the quality of the channels used for data transmission between transmitters and receivers in an OFDM system [135], [136].

Y. Liu *et al.* [125] proposed a DL framework to estimate sensing and communication channels for intelligent reflecting surfaces (IRS). This framework employs two DNNs. The first DNN is designed to make an estimation of the sensing channel on the base station using the feed-forward layer, and the second DNN is designed to estimate the communication channel on UE using CNN. A designed input-output pair of sensing and communication channels constructs the dataset. The proposed method will be evaluated using normalized mean square error (NMSE) and compared with the baseline using a least squares estimator. Compared with the benchmark scheme, the proposed method shows better generalization ability and greatly improves the performance of NMSE.

Z. Chen *et al.* [126] proposed an angel-based sensing turbo variational Bayesian inference (AS-TVBI) to improve channel estimation and target sensing on self-sensing IRS-aided millimeter wave ISAC system. This idea is to overcome the problem of passive IRS device-free sensing that may cause severe path loss due to multiple signal reflections that can degrade the sensing performance. There are two phases

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to get coarse and refined sensing/channel estimation results. To overcome the problems of joint sensing and channel estimation, AS-TVBI designed each stage. The simulation results show the effectiveness of the proposed method.

Y. Liu *et al.* [127] Proposed channel estimation in multi-user ISAC assisted by the IRS system using an extreme learning machine (ELM). Channel estimation problems can occur in such systems because passive IRS cannot process signals properly and interference occurs between communication and sensing signals. To simplify the solution, the channel estimation problem is divided into two sub-problems: direct channel estimation and reflection channel estimation. Based on this scheme, the sensing and communication channels of the target and uplink users will be estimated by the ISAC BS, while the downlink communication channels of each user will be estimated individually. The NN consisting of two ELMs is in the downlink user and the ISAC BS to estimate the sensing and communication channels. From the simulation result, the proposed ELM-based framework performs better from least-squares, CNN, and feedforward neural network (FFNN), with reduced training complexity and faster training time.

Y. Liu *et al.* [128] utilize CNN for channel estimating for IRS-assisted ISAC, illustrated in Figure 9. Three stages are used to constitute several sub-problems to separate the estimation problem: estimation of the sensing and direct communication channels, estimation of reflected communication channels, and estimation of the reflected sensing channel. To solve three sub-problems, two CNN-based channels estimation is proposed. The first CNN was used to solve the problem of direct sensing and communication channels, and the second CNN was used to solve the problem of reflected sensing and reflected communication channels. Based on the simulation result, the proposed CNN has better NMSE over the least-square baseline scheme.

2) Waveform or Beamforming Design

Waveform design is a crucial technology as it determines a system's performance limits [137]. The ISAC system aims to simultaneously perform sensing and communication using the same resource platform, including waveform and beamforming. Proper waveform design and beamforming can enable efficient utilization of resources to achieve both functions effectively [138]. As in [139] the authors designed beamforming to achieve high communication rates and detect passive targets, allowing communication and sensing to operate more effectively together.

Q. Qi *et al.* [129] proposed the ISAC system waveform and beamforming design based on DL. Due to the sharing of resources for sensing and communication, mutual interference between them can occur, which can lead to overall performance degradation. To overcome this problem, ISACNN is proposed to optimize sensing signal waveform and communication receive beamforming. ISACNN consists of 4 fully-connected neural networks (FCNN). Based on theoretical analysis and numerical results, it shows that the proposed method is more effective than the baseline method.

In another study, Q. Qi *et al.* [130] has modified ISACNN by adding the CNN inside the architecture of ISACNN. CNN is added to extract features of the input vector, and then FCNN will integrate feature information from CNN which will produce vector θ and scale scalar η. The output of FCNN will be sent to the lambda layer to produce the output signal. The modified ISACNN is effective and robust, as proven by theoretical analysis and simulation results.

L. Xu *et al.* [131] proposed deep reinforcement learning (DRL) to design beamforming transmit for integrated automotive radar sensing and communication. DRL is utilized to learn a quantized vector of beamforming transmission for a sparse array transmission in automotive radar ISAC systems. Automotive radar learns the current reflecting the difference between mainlobe peak and sidelobe peak levels in radar sensing mode or user feedback in communication mode and intelligently adjusts its beamforming vector in a way that interacts with the environment. Simulation results confirm that the proposed approach effectively handles large action space dimensions without requiring extensive action search.

3) Signal Processing

In an ISAC system, the receiver must be able to extract valuable information from the communication signal and simultaneously estimate the state of the target or target-related parameters from the echoes. These two tasks will likely be performed simultaneously, which can result in mutual interference and create challenges in ISAC system design [140].

Z.Zhang *et al.* [13] proposed DL methods for ISAC in vehicular networks. This paper proposed two model DL for multi-user demodulation using DNN and multi-target sensing using YOLOv5 [141]-SORT based on CNN. DNN-based demodulation demonstrates better than Successive Interference Cancellation (SIC), and the tracker based on peak detection, K-means clustering, and PHD filter outperforms the baseline tracker.

W. Jiang *et al.* [132] introducing ISAC-NET, DL-based that adopts a block-by-block method for signal processing to improve sensing and communication performance. ISAC-NET is proposed as an ISAC signal processing optimization scheme that jointly processes the pilot and data signal. Simulations show that ISAC-NET performs better than traditional communication and sensing signal demodulation.

Y. Wu *et al.* [133] proposed sensing integrated discrete Fourier transform spread orthogonal frequency division multiplexing (SI-DFT-s-OFDM) system and DL-powered receiver design for terahertz (THz) ISAC system. Two DLs are developed at the receiver for communication and sensing. In the sensing part, DL is used to estimate velocity and range. In the communication part, DL is used to recover data symbols. Based on simulation results, the proposed DL method has enhanced the sensing and communication performance and is robust against phase noise, Doppler effects, and multi-target estimation.

V. FUTURE RESEARCH

The application ISAC with ML has been surveyed above, and from those articles, several points can improve the performance of the applications for future research direction.

A. DATASET QUALITY

First of all, the quality of the dataset must be improved. It can add more data and more categories; for example, GPS data can be added to the localization dataset to improve accuracy. In [142], proposed selected a subset of UEs with accurate position estimated using GPS to be anchors to localizing the target; this method proved its effectiveness with its numerical results. Besides that, the preprocessing step can take the role in improving the performance of model ML/DL, such as looking for the correlation between data or reducing the dimensional data, it can improve the quality of data that can be fed into ML, leading for better performance and more reliable result.

B. COMPLEX ENVIRONMENT

Second, improving the complexity of the environment. It can be adding multiple objects to sensing or adding more sensing sources to make it more reliable in daily life applications. Detecting multiple objects with a model that is trained for one object seems difficult because the model is prepared to detect one object, whereas to detect multiple objects, it must be retrained with better data and in accordance with real conditions. In [143] proposed EasyCount, crowd counting using WiFi. EasyCount can be used for counting 0-6 people, and you just need one person to do the simple calibration. So, multi-object sensing with ISAC is possible. Most of the surveyed papers use only one sensing source. Adding more sensing sources can be more reliable because, in some real-life conditions, there is more than one wireless source in one place. With more sensing sources, it can make an interference for the main sensing source and make a reliable dataset for training ML and can improve its robustness.

C. SIGNAL VARIATION

Third, apart from improving the complexity of the environment, using other signal variations, such as different frequencies, can be used to enhance ML performance so that it can adapt better. For example, in the study surveyed previously [133], By using the low THz scenario as a dataset, the resulting model does not necessarily work well for the high THz scenario. This is because, at high THz, atmospheric effects further weaken the propagation of THz waves, the Doppler shift worsens, and the saturation output value of the power amplifier becomes even lower. This development aims to improve the performance and durability of the model created.

D. MULTIMODAL SENSING

Fourth, combining with other technologies like IoT to improve the quality of service for users and make it more reliable. With IoT technology, ISAC can be combined with various other types of sensing, thereby enhancing the overall user experience. There are seven scenarios and 34 use cases ISAC for IoT that have been discussed in [144], including remote sensing, environment monitoring, human-computer interaction, sensing as a service, vehicle to everything, smart home, and in-cabin sensing. in [145] proposed ISACoT as a general framework covering the time, space, frequency, and protocol aspects of the problem.

E. ISAC-AIDED DIGITAL TWIN

Digital Twin (DT) is a promising technology with the potential to shape the future of industry and society [146]. DT is an experimental technology designed to replicate physical systems such as elements, functions, operations, and dynamics into a digital form that allows for better control, testing, analysis, and prediction. DT has already been utilized in various fields, such as healthcare [147]–[149], manufacturing [150], [151], and smart cities [152], [153]. ISAC can be applied to DT with its capability to sense the environment and communicate effectively, which reduces the need for additional hardware and improves the efficiency of sensing data transmission [154]. Moreover, ISAC can be used to reduce processing latency with the help of Deep Reinforcement Learning (DRL) as shown in [155].

VI. CONCLUSION

We have provided a comprehensive survey of ISAC systems enhanced by ML. We summarized concepts of ISAC based on various configurations, sensing sources used in ISAC, and real-world applications of ISAC. We highlighted ML methods that are applicable to this field and their potential to enhance ISAC systems. We reviewed several practical applications of ML in ISAC systems, emphasizing improvements in sensing and signal optimization and highlighting the technology's advantages in enhancing performance and capabilities. By providing this comprehensive overview, we hope our survey can help readers understand ISAC and ML by showing the potential benefits of integrating ML with ISAC to inspire further research and stimulate more widespread applications.

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