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RESEARCH ARTICLE

Machine Learning Innovations in LoRaWAN: A Comprehensive Survey of Technology, Trends, and Applications

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ABSTRACT

The integration of Machine Learning with Low Power Wide Area Network (LPWAN) technologies, particularly LoRaWAN (Long Range Wide Area Network), is transforming the Internet of Things (IoT) landscape by enhancing network performance, scalability, and intelligence. LoRaWAN, an open LPWAN standard developed by the LoRa Alliance, enables long-range communication with minimal power consumption. Although LoRaWAN provides low-power and long-range communication capabilities, it still faces several challenges, including scalability limitations, energy efficiency concerns, resource allocation issues, limited coverage, and susceptibility to interference. Recent advancements in machine learning, deep learning, and federated learning have introduced innovative solutions to address these challenges, fostering the development of intelligent, adaptive, and efficient LoRaWAN networks. This survey also presents a comparative analysis of various LPWAN technologies by examining key parameters such as bandwidth, data rate, coverage, and other critical factors. Furthermore, it explores the performance metrics and practical applications of LoRaWAN across various domains, emphasizing the impact of ML-based approaches. By synthesizing recent research findings and real-world implementations, this survey provides a comprehensive understanding of how ML can significantly enhance the performance and capabilities of LoRaWAN networks.

1 | Introduction

The IoT users are in a new era of connectivity by enabling everyday objects to interact, cooperate, and exchange information via the Internet. IoT devices primarily use sensors to collect data, analyze it locally or remotely, and take action based on the insights obtained. This seamless integration of the physical and digital worlds enables innovative solutions across various fields, including healthcare, transportation, agriculture, and environmental monitoring [1]. With the rapid growth of the IoT sector, LPWANs have emerged as a leading low-power, long-range communication technology. LoRa, NB-IoT, LTE-M, and Sigfox are the main LPWAN systems competing for large-scale IoT deployments, as shown in Figure 1 [2]. Traditional wireless networks such as Wi-Fi and cellular are often unsuitable for IoT applications due to their high power consumption, limited coverage, and cost constraints. In this context, LPWAN solutions provide energy-efficient, long-range connectivity specifically designed to meet IoT deployment requirements. They enable battery-powered devices

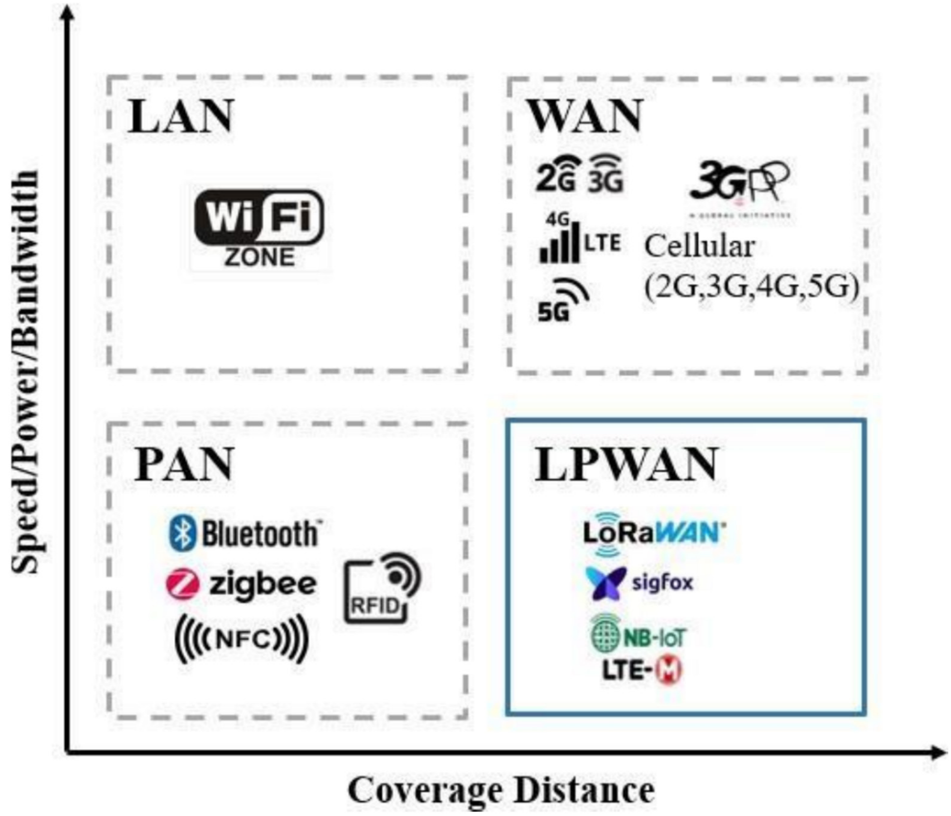

FIGURE 1 | Comparison of speed, power, and bandwidth versus coverage distance for LPWAN technologies [2].

to operate in remote or hard-to-reach areas without frequent battery replacements by transmitting data over long distances using low-power communication [3].

To understand the advantages and disadvantages of each technology, we examine key factors such as frequency bands, data rates, coverage distance, security, and other essential parameters, as summarized in Table 1.

Another LPWAN technology, Sigfox, has a strong emphasis on long-range communication. Using ultra-narrowband transmission, it can achieve coverage of several tens of kilometers per base station, which significantly reduces power consumption and extends battery life [4]. Within the licensed spectrum of existing cellular networks, NB-IoT (Narrowband IoT) provides a reliable solution with good penetration both indoors and outdoors and low power consumption, ensuring a long battery life for IoT devices [5]. LTE-M (Long-Term Evolution for Machines) leverages current LTE infrastructure to combine wide coverage with higher data rates. Compared to LoRa and Sigfox, LTE-M consumes more energy but can support a wider range of applications, including those requiring mobility and voice communication [6]. Depending on the use case, each LPWAN technology offers an optimal balance between coverage distance and power consumption, as shown in Figure 2. For example, LoRa and Sigfox provide long-range, low-power connectivity suitable for remote and rural monitoring, while NB-IoT and LTE-M enable reliable, higher-bandwidth communication in more demanding environments.

1.1 | Related Survey

This section explores relevant works on LoRaWAN networks integrated with machine learning (ML), spreading factor (SF) optimization, scalability, energy efficiency, and interference from 2016 to 2025, as summarized in Table 2 and illustrated in Figure 3. The key studies are as follows: Augustin et al. [7] conducted a survey on LoRa modulation, covering aspects such as symbol rate, transmission rate, and frame structure. A testbed was constructed to investigate overall network functionality. Lavric et al. [8] assessed LoRa technology with respect to IoT requirements, discussing existing challenges and the need for potential solutions. Sinha et al. [9] provided a comparative and comprehensive analysis of low power wide area (LPWA) technologies, such as LoRa and NB-IoT, in terms of MAC protocols, physical characteristics, and network architecture. Network coverage and Quality of Service (QoS) were also examined. Saari et al. [10] explored ongoing research and practical applications of LoRa. Haxhibeqiri et al. [11] analyzed physical and network layer performance and provided a SWOT evaluation.

Abdelfadeel et al. [12] investigated the effects of multipath reflections, performance variations between indoor and outdoor communication, and the impact of terrain elevation on channel loss and packet delivery rate. Recent research on LoRaWAN highlights opportunities for IoT development, including simulators, performance challenges, and proposed solutions [13, 14], emphasizing multiple challenges and presenting feasible strategies [15]. Studies also address LPWAN technologies and their associated

TABLE 1 | Overview of LPWAN technologies.

Parameter	LoRaWAN	Sigfox	NB-IoT	LTE-M	Dash7
Frequency bands	Sub-GHz (433 MHz, 868 MHz, 915 MHz)	ISM Band (868 MHz in Europe, 902 MHz in the US)	Below 1 GHz (varies by region)	Below 2 GHz (varies by region)	ISM Band(433 MHz, 868 MHz, 915 MHz)
Data rates	Varies (from a few bps to several kbps)	100 bps to 1 kbps	Tens of kbps to hundreds of kbps	Hundreds of kbps to Mbps	9.6 kbps to 167 kbps
Coverage range	Several km in urban areas, over 10 km in rural areas	Extensive coverage (tens of km per base station)	Deep indoors, underground penetration	Extensive coverage with LTE infrastructure	500 m to 2 km in urban, up to 5 km in rural
Localization	Yes	Yes	No	May varies	Yes
Security	Built-in 128-bit AES encryption	Built-in 128-bit AES encryption	LTE security	LTE security	Built-in 128-bit AES encryption
Energy lifespan	Over 10 years	Exceeding 10 years	10 years	Approx. 5 years	Close to 10 years
Deployment	Open	Private	Open	Open	Private
Spectrum	Unlicensed	Unlicensed	Licensed	Licensed	Unlicensed
Modulation	Chirp Spread Spectrum (CSS)	UNB (Ultra Narrow Band)	OFDM (Orthogonal Frequency Division Multiplexing)	Quadrature Phase Shift Keying (QPSK)	Gaussian Frequency Shift Keying (GFSK)
Dual communication	Supported	Not supported	Supported	Supported	Supported
Latency	Variable, typically less	Variable, typically less	Less	Less	Less
Energy	Very energy-efficient	Ultralow power	Moderate	Higher power consumption	Low to moderate
Cost	Very low	Low	Moderate to high	High	Low

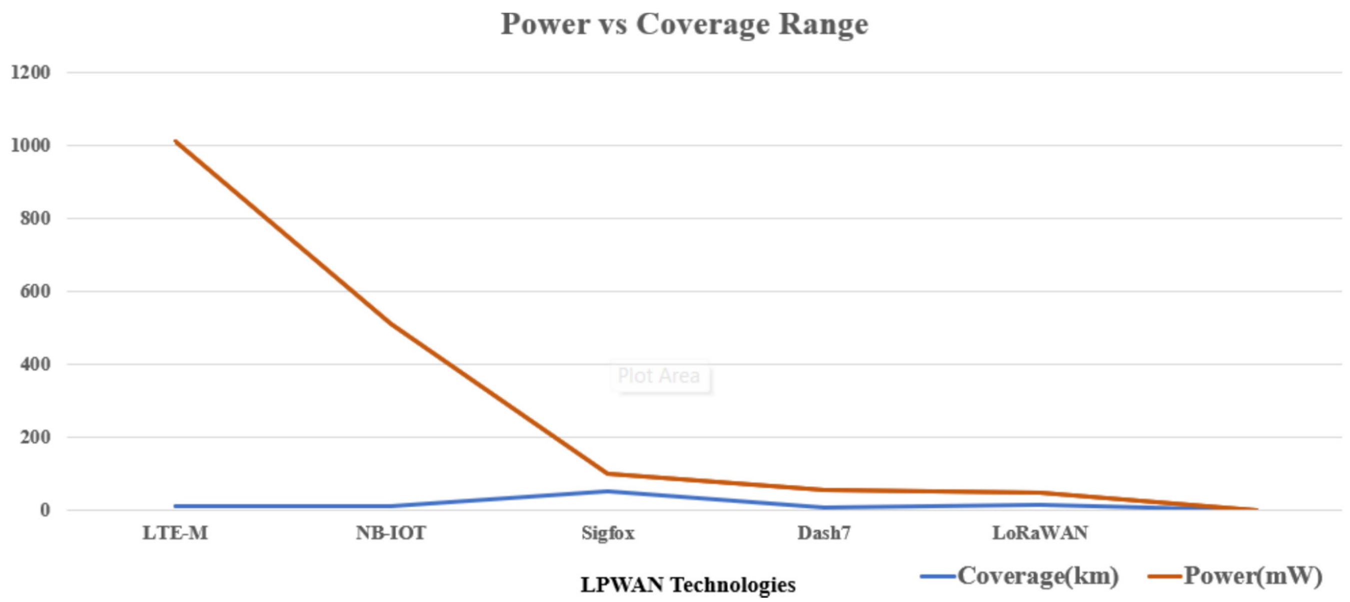

FIGURE 2 | Coverage range of LPWAN technologies.

challenges [16, 17, 22, 23], as well as providing overviews of LoRa networks, implementation difficulties, and supported applications [19, 25]. To improve network performance, adaptive data rate (ADR) mechanisms have been employed to enhance scalability [18], while ML techniques are increasingly applied to optimize LoRaWAN performance [26, 27]. A hybrid CNN-LSTM + TinyML framework enables efficient on-device SF prediction by capturing spatial-temporal features with minimal power consumption [31]. Furthermore, the integration of aerial access networks (AAN), federated learning (FL), and hybrid LoRa P2P/LoRaWAN supports scalable, privacy-preserving remote environmental monitoring with flexible and resilient connectivity [32].

Numerous aspects of the LoRaWAN network have been examined in recent studies, including modeling tools, ADR optimization, PHY/MAC layer performance, and security. Table 3 presents the proposed survey of the LoRaWAN network. This survey fulfills a critical need by providing a comprehensive assessment of challenges, simulation tools, applications, and the integration of ML techniques in LoRa/LoRaWAN.

1.2 | Research Questions

LoRaWAN research has expanded from basic optimization to ML and DL solutions for higher scalability and energy efficiency. Figure 4 illustrates key research questions addressing this evolution, comparative performance with other LPWANs, and future improvements in rural connectivity.

1.3 | Motivation and Contribution

This survey presents the various features of LPWAN technologies such as LoRaWAN, NB-IoT, Sigfox, LTE-M, and Dash7, highlighting key parameters including frequency, localization, energy efficiency, and coverage range. The main contributions of this survey are summarized as follows:

- Analysis of LoRaWAN challenges: We provide an in-depth analysis of the key challenges faced by LoRaWAN, including scalability, energy utilization, resource allocation, coverage area, and interference, and discuss how these can be addressed using ML, deep learning (DL), and FL techniques. A key novelty of this survey is its focus on FL as an emerging paradigm for LoRaWAN optimization.
- Performance evaluation of ML-enhanced LoRaWAN: We review performance measurements of LoRaWAN enhanced with ML techniques and present current solutions addressing energy consumption, coverage range, and error correction challenges that affect network performance.
- Historical literature review (2016–2025): We provide a chronological overview of relevant LoRaWAN research, highlighting the evolution from conventional approaches to state-of-the-art ML/DL/FL solutions, and presenting the various ML models applied to LoRaWAN networks.
- Simulation tools and applications: We offer a comprehensive overview of simulation tools used in LoRaWAN research and their integration with ML/DL/FL techniques across diverse domains, including environmental monitoring, air quality monitoring, healthcare, agriculture, and industrial automation.

1.4 | Paper Organization

Figure 5 illustrates the structure of the remaining sections of this paper. Section 1 presents the characteristics of LoRa and LoRaWAN technologies. Section 2 describes the ML/DL/FL techniques applied in LoRaWAN networks. Section 3

TABLE 2 | Existing survey of LoRa and LoRaWAN from 2016 to 2025.

Paper	Year	Inferences
[7]	2016	The physical and data connection layers are evaluated by the field testing
[8]	2017	This paper analyzes the problems and constraints of IoT concepts, focusing on LoRa technology.
[9]	2017	Provide a thorough analysis of LoRa and NB-IoT in terms of MAC protocol and physical characteristics.
[10]	2018	This study highlights the most current developments in LoRa studies along with useful applications.
[11]	2018	Incorporating the current safety and dependability systems and along with the difficulties, a SWOT evaluation is also provided.
[12]	2019	Examined on path losses, multipath reflection, and packet rates for delivery
[13]	2019	They include the latest research in the literature and the LoRaWAN network, and provide chances for development.
[14]	2019	This includes a discussion of the assessed simulators, along with providing suggestions for IoT applications.
[15]	2019	Highlighting various issues and ways to solve them for Internet of Things applications. The standards and foundations for 5G communications technologies—LoRaWAN, NB-IoT, Sigfox, and LTE-M are compared, and their possible applications for WSN are examined.
[16]	2019	The standards and foundations for 5G communications technologies—LoRaWAN, Sigfox, LTE-M, and NB-IoT are compared, and their possible applications for WSN are examined.
[17]	2019	An overview of current wide-area low-power technologies and practical advice to support the widespread installation of LPWA networks.
[18]	2020	Highlight new adaptive data rate methods as an optimizing strategy to boost scalability, productivity, and energy conservation.
[19]	2020	Provide a detailed overview of LoRa networks, covering novel approaches and the technical difficulties in implementing LoRa networks.
[20]	2020	Suggested routing methods like tree topology and the flooding approach to enhance LoRaWAN reliability and enable multihop communication.
[21]	2021	ML techniques are employed to propose optimal solutions in LoRaWAN.
[22]	2021	Examine the different operational aspects of NB-IoT and LoRaWAN networks.
[23]	2022	It compares five LPWAN technologies, showing NB-IoT outperforms in latency and quality, while LoRa/LoRaWAN and SigFox lead in device lifespan, capacity, and cost. It further provides a detailed overview and analytical tools for LoRa and LoRaWAN.
[24]	2022	The most essential wireless techniques for connecting to networks are described, and current cloud-based and open-sourced methods to handle data are explored.
[25]	2022	Provides a thorough overview of LoRa, including its evaluation, communication, safeguards, and supported applications.
[26]	2023	ML methods have been applied to addressing resource allocation issues
[27]	2023	In order to solve the scalability issues, they examined the most recent PHY and MAC layer technologies. Modulation techniques, network features, interference, and collision are the major concerns considered in the LoRaWAN.
[28]	2024	This research carefully investigates the waveform structure of LoRa substitutes and suggests both noncoherent and coherent methods of detection for particular systems.
[29]	2024	This research sheds the spotlight on what future IoT communication methods for mining will need, as well as where LoRaWAN may be used in both surface and underground mining. It helps in determining their track patterns of strengths, weaknesses, and reliability.
[30]	2025	First large-scale real-world analysis (30,000+ devices) of LoRaWAN ESP prediction; introduces ML-driven tool for dynamic and automated network optimization.
[31]	2025	Proposes a hybrid CNN-LSTM + TinyML framework for spreading factor prediction.
[32]	2025	Proposes an integrated system combining Aerial Access Networks (AAN), FL, and hybrid LoRa P2P/LoRaWAN for remote environmental monitoring.

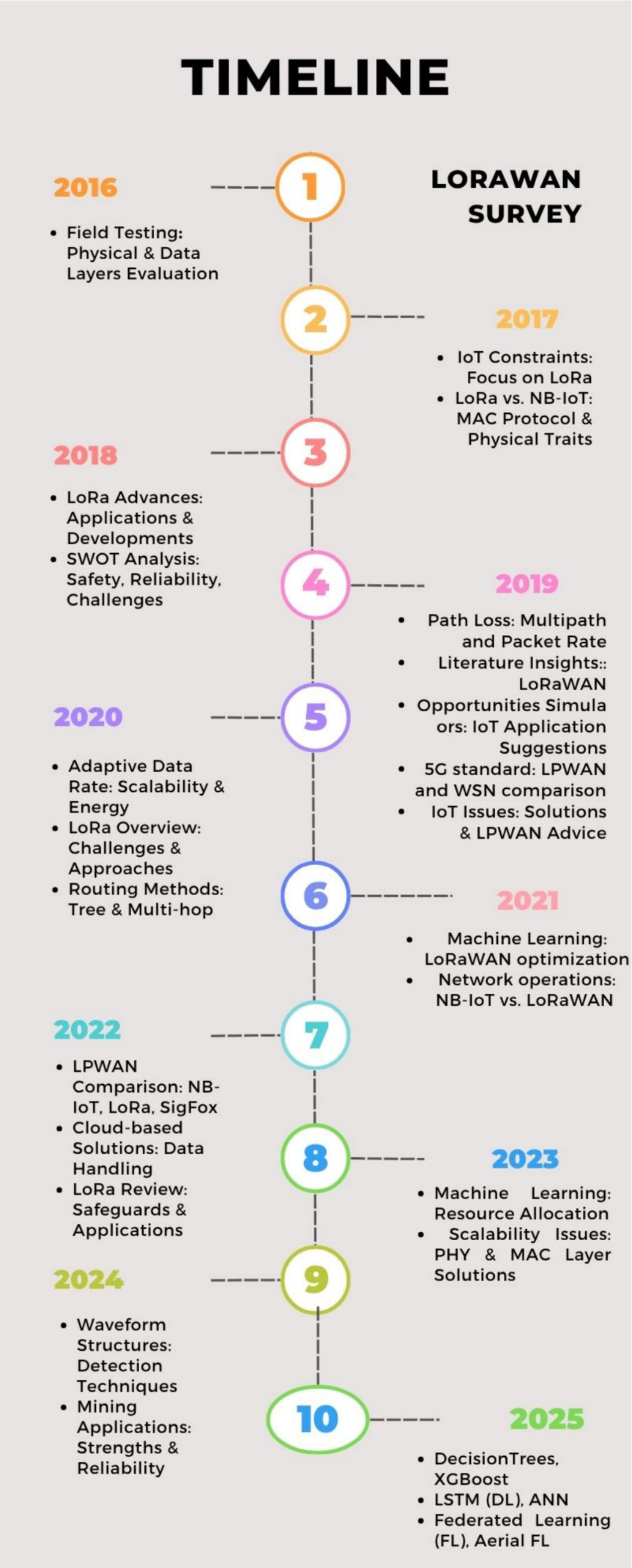

FIGURE 3 | Research survey of LoRaWAN.

explains the performance measurements and current solutions for LoRaWAN. Section 4 explores the applications of LoRaWAN across various domains, and Section 5 concludes the paper by highlighting open challenges and future research directions.

2 | LoRa AND LoRaWAN

2.1 | Features of LoRa and LORAWAN

2.1.1 | LoRa Physical Layer

One of Semtech's most significant innovations in wireless communication is LoRa (Long Range), which offers extremely low power consumption and long transmission ranges between IoT devices and gateways [33]. Its ability to support long-range communication with minimal energy usage makes it ideal for large-scale IoT deployments across diverse environments. A key advantage of LoRa is its Chirp Spread Spectrum (CSS) modulation, which ensures reliable communication even in noisy environments and over extended distances. The PHY layer format, shown in Figure 6, consists of a preamble for receiver synchronization, a PHY header carrying payload metadata, the payload data, and a CRC for error-checking to ensure data integrity [27].

Its versatility has facilitated integration into a wide range of industries, including utilities, smart cities, industrial IoT, and agriculture. LoRa technology possesses several key characteristics that determine its reliability and suitability for different applications. The primary variables to consider include bandwidth, chirp rate, error correction rate, and transmission power. Understanding these characteristics and their interactions is essential for optimizing LoRa network deployments. Bandwidth refers to the range of frequencies over which the electrical signal is spread. Typical LoRa bandwidths are 125, 250, and 500 kHz. The SF is defined as the ratio between the symbol rate and the chip rate, ranging from SF7 to SF12. Higher SFs increase signal range and robustness, but they also lengthen transmission time and reduce data rates. The relationship is expressed as follows:

$$\mathrm{RS} = \mathrm{BW} / 2\mathrm{SF}$$

RS stands for symbol rate, BW for bandwidth, and SF for SF. The coding rate influences the amount of correction of errors given to the data. LoRa provides coding rates of 4/5, 4/6, 4/7, and 4/8. A greater coding rate enhances error correction while lowering the actual data rate. The equation is shown below,

$$R = \mathrm{SF} \times \mathrm{BW} / 2^{\mathrm{SF}} \times \mathrm{CR} / \mathrm{CR} + 4$$

where R is the data rate, and CR is the coding rate. The time on air refers to how long it takes to send a packet. It is determined by the SF, the bandwidth, the coding rate, and the payload length.

$$T = (\mathrm{Np} + \mathrm{Nh} + \mathrm{Nf} + 4.25) / \mathrm{Rs}$$

where T is time on air (seconds) and Np is the quantity of payload bytes. Nh denotes the amount of header bytes, whereas Nf represents the number of fixed-overhead bytes.

2.1.2 | LoRaWAN MAC Layer

LoRaWAN network architecture is typically organized in a star-of-stars topology, comprising key components such as end-node sensors, gateways, network servers, and application servers, as

TABLE 3 | Overview of current studies conducted by LoRaWAN.

Papers	1	2	3	4	5	6	7	8	9	10
[7]	✓	✓	×	×	✓	×	✓	×	✓	×
[8]	✓	✓	×	×	×	×	✓	×	✓	✓
[9]	✓	✓	✓	×	✓	×	×	×	×	×
[10]	✓	×	×	✓	×	×	×	×	×	✓
[11]	✓	×	✓	✓	✓	×	×	✓	✓	✓
[12]	×	×	×	✓	×	×	×	×	✓	×
[13]	✓	✓	✓	✓	✓	×	×	×	×	✓
[14]	×	×	×	×	×	×	×	✓	×	×
[15]	✓	×	✓	×	×	×	✓	×	×	×
[16]	×	✓	×	×	✓	×	×	×	×	×
[17]	×	✓	✓	✓	×	×	×	×	✓	✓
[18]	✓	×	✓	✓	✓	✓	✓	×	✓	×
[19]	✓	✓	✓	×	×	×	✓	×	×	✓
[20]	×	×	✓	✓	×	×	×	×	×	×
[21]	✓	×	✓	✓	×	✓	✓	×	✓	✓
[22]	✓	✓	✓	✓	✓	×	×	×	✓	✓
[23]	✓	✓	✓	✓	×	×	✓	✓	×	×
[24]	✓	✓	✓	✓	✓	×	×	✓	✓	×
[25]	✓	✓	✓	✓	✓	×	×	×	✓	✓
[26]	✓	✓	×	✓	×	✓	×	✓	×	✓
[27]	✓	✓	✓	✓	✓	×	✓	×	✓	✓
[28]	×	×	×	✓	✓	×	×	×	✓	×
[29]	✓	✓	✓	✓	×	×	×	×	✓	✓
[30]	×	×	×	×	×	✓	✓	×	✓	✓
[31]	✓	×	×	✓	×	✓	×	×	×	✓
[32]	×	×	✓	✓	×	✓	×	×	✓	✓
Proposed survey	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: 1—Lora/LoRaWAN architecture, 2—LPWAN technologies, 3—Challenges of LoRaWAN network, 4—LoRaWAN methodology, 5—PHY/MAC layer, 6—ML/DL/FL techniques, 7—LoRaWAN solutions, 8—Simulation tools, 9—Performance analysis, 10—application.

illustrated in Figure 7. The LoRaWAN communication protocol and system framework are shown in Figure 8. LoRa modulation enables end nodes to collect and transmit sensor data to gateways. Gateways act as intermediaries between end devices and the network server, receiving LoRa signals from the nodes and forwarding them to the server via conventional IP-based backhaul connections. The network server manages the overall network operation by routing messages between the end nodes and the application servers, ensuring security, and managing device operations. The application server processes and analyses the data received from end nodes, providing the required services to users. These services may include data visualization, storage, analysis, and triggering actions based on the collected information.

The MAC layer format, Figure 9 consists of the MAC header (MHDR), device address (DevAddr), frame control (FCtrl), frame counter (FCnt), optional MAC commands (FOpts), frame port (FPort), frame payload (FRMPayload), and a message integrity code (MIC) to ensure the confidentiality of data and authentication [13].

LoRaWAN, a network protocol designed for long-range communication, classifies end devices into the following three categories: Class A, Class B, and Class C, as illustrated in Figure 10. Each class addresses different application requirements and is characterized by distinct energy consumption, latency, and communication mechanisms.

2.1.2.1 | Class A Devices. Class A devices are highly energy-efficient and are ideal for battery-powered applications. They operate using a simple communication mechanism, where each device transmits an uplink message to the gateway and then opens a short downlink reception window to await an acknowledgment. This design ensures minimal power consumption, as the device spends most of its lifetime in a sleep state, periodically waking up to transmit data and briefly listen for responses. Class A is suitable for applications where downlink communication is not time-critical, such as environmental monitoring or periodic sensor data reporting. Devices transmit (TX) whenever data is available and subsequently open two reception windows at predefined intervals following each transmission [23].

- TX (Transmit): The device transmits an uplink signal to the gateway.

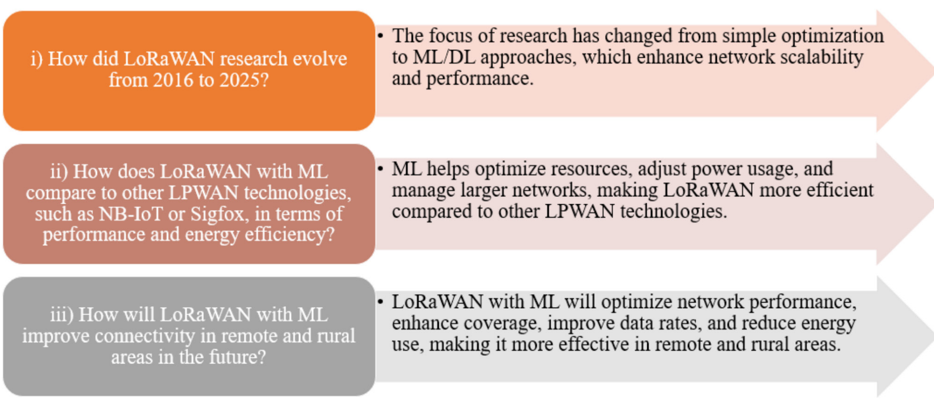

FIGURE 4 | Research questions for this survey.

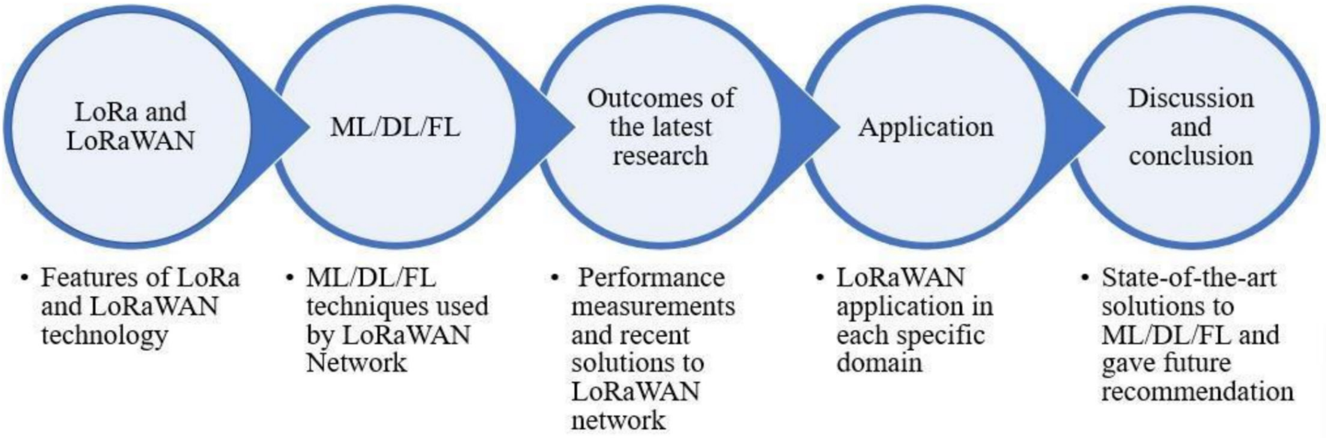

FIGURE 5 | Organization of this survey.

Preamble (8 symbols)	PHY Header (8 bits)	Payload (upto 255bytes)	CRC (16 bits)

FIGURE 6 | PHY Layer frame structure.

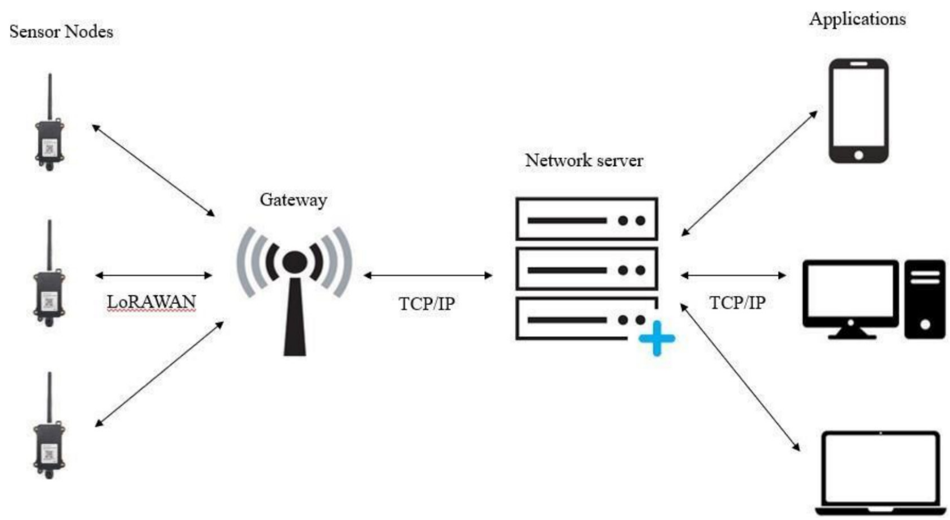

FIGURE 7 | LoRaWAN network architecture [13].

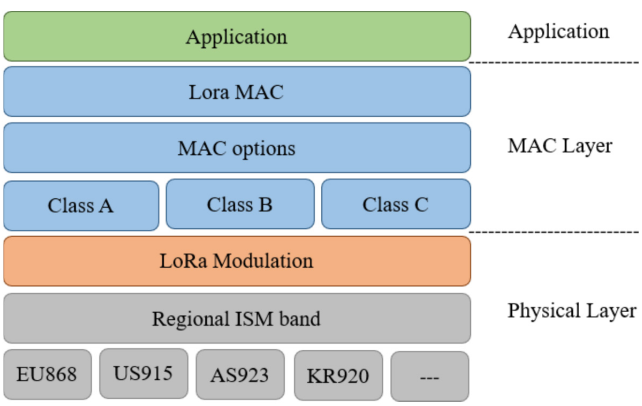

FIGURE 8 | The LoRaWAN communication protocol and system framework [21].

- RX1 (Receive Window 1): opens exactly a moment after the TX ends. The gadget is listening for a downlink signal.
- RX2 (Receive Window 2): Opens for 2 s after the TX ends if no packets were received during RX1.

2.1.2.2 | **Class B Devices.** Class B devices extend the functionality of Class A by introducing scheduled downlink opportunities. In addition to the randomized uplink and downlink windows of Class A, Class B devices open additional downlink slots at predefined intervals. These scheduled slots are synchronized with the network through periodic beacons transmitted by the gateway. This mechanism enables more frequent downlink communication while maintaining relatively low power consumption. Class B is well-suited for applications that require regular downlink updates or network-initiated

MHDR (8 bits)	DevAddr (32 bits)	FCtrl (8 bits)	FCnt (16 bits)	Fopts (upto 15bytes)	Fport (8 bits)	FRM Payload (variable)	MIC (32 bits)

FIGURE 9 | MAC layer frame structure.

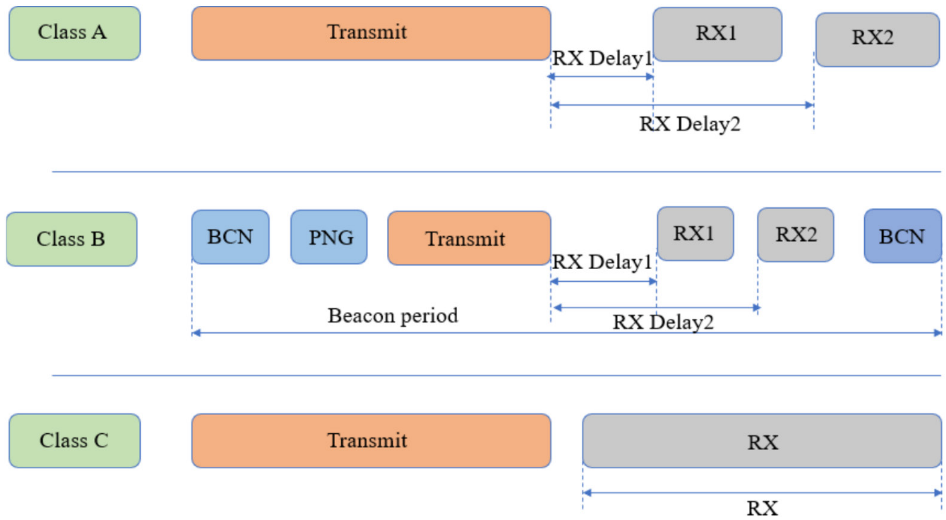

FIGURE 10 | LoRaWAN classes demonstrate distinct network utilization characteristics [21].

control and management operations, such as progress tracking or remote actuation commands [23].

- The gateway sends out a beacon to synchronize the network. This occurs at regular intervals (e.g., every 128 s).
- TX: The device transmits an uplink data.
- Ping Slot: Occurs at predetermined periods, synchronized with the beacon, enabling the device to acquire downlinks at regular intervals.

2.1.2.3 | Class C Devices. Class C devices are designed for applications that require continuous downlink availability. Their receivers remain active almost constantly, switching off only briefly during uplink transmissions. This configuration allows the network to deliver downlink messages with minimal latency, making Class C ideal for real-time applications that demand rapid response. However, the continuous listening mode results in higher energy consumption, which makes Class C devices more suitable for mains-powered applications, such as smart grid systems or automated industrial processes [23].

- TX: The device transmits an uplink data.
- Continuous RX: Except for transmission, the device is continually monitoring for downlink signals.

2.2 | Challenges in LoRa and LoRaWAN Networks

Integrating a large number of LoRaWAN nodes presents several challenges during deployment and operation, including scalability, energy consumption, resource allocation, coverage, and interference, as summarized in Table 4.

2.3 | Methodology

This section outlines the methodical approach used to conduct a comprehensive study of LoRaWAN networks integrated with ML. The primary objectives of this study are to systematically evaluate existing literature, categorize ML approaches based on their usage and performance, identify challenges in LoRaWAN networks, and recommend potential future research directions. To collect relevant literature, we conducted a systematic review of multiple databases, including IEEE Xplore, SpringerLink, ACM Digital Library, and Google Scholar. A multifaceted search strategy was employed using keywords and combinations such as “LoRaWAN” AND “Machine Learning”, and “IoT” AND “LoRaWAN” AND “ML”. The selection criteria focused on peer-reviewed journal articles, conference papers, and research studies published between 2021 and 2025 that emphasized the application of ML, DL, and FL in LoRaWAN networks, as illustrated in Figure 11.

We developed a classification framework to categorize ML approaches based on their application in LoRaWAN networks, including supervised learning (labeled data), unsupervised learning (unlabeled data), and reinforcement learning (RL). For each selected study, we extracted details regarding the ML approach, the specific algorithm used, the primary application, and the datasets utilized. This framework enabled a systematic classification and comparison of the various ML techniques applied to LoRaWAN. A total of research articles

TABLE 4 | Challenges faced by LoRaWAN network.

Authors	Challenges	Discussions
Mikhaylov et al. [34]	Scalability	LoRa-modulated transmission rates are less impacted by interference, emphasizing the scalable network-level operation of the technology.
F. Van den Abeele et al. [33]		The delivery ratio of verified upstream traffic is adversely affected by downstream traffic, according to a scalability analysis of the LoRaWAN ns-3 module.
Jouhari et al. [27]		Solutions to the MAC and physical layers concentrate on methods incorporating frequency channel assignments, logical channels, and spreading factors.
Lavric et al. [35]		Strategies to lower the rate of collisions and enhance the communication channel's capability
Farhad et al. [36]		Employing both confirmed and unconfirmed modes of communication to address the issue of network scalability
Bouguera et al. [37]	Energy utilization	Utilizing a full energy model for communicating sensors in order to determine the lifespan of each sensor node and the energy usage of LoRaWAN Class A.
Cheong et al. [38]		The energy loss can be computed using Ohm's Law.
Finnegan et al. [39]		The energy usage of the SX1272 in various states was determined to accurately simulate the electrical energy use of LoRaWAN Class A.
Maudet et al. [40]		An energy consumption model is created using the network's node count, collision probability, and retransmission frequency.
Khalifeh et al. [41]		The network's power consumption significantly decreased when the reinforcement learning method was used.
Minhaj et al. [42]	Resource allocation	To solve the contextual bandit problem, SF is distributed among the devices by RL and the electrical power is distributed centrally through supervised ML.
Romero et al. [43]		The Collision Avoidance Resource Allocation (CARA) algorithm aids in boosting the system's capacity.
Ta et al. [44]		The EXP3 (Exponential Weights for Exploration and Exploitation) algorithm is used for spreading factor selection.
Moraes et al. [45]		CORRECT heuristic is used to provide allocation in LoRaWAN by reducing collisions.
Tellache et al. [46]		Deploying a multiagent DRL that distributes transmission power (TP) and spreading factor (SF)
Apriantoro et al. [47]	Coverage area	With up to eight blank spots, the network range and signal strength are both extremely appropriate.
Nashiruddin et al. [48]		The link budget is determined first, and then a simulation using Forsk Atoll 3.3.2 is used to simulate coverage.
Paternina et al. [49]		The spreading factor and coding rate were SF10-CR4, with an estimated range of 7–10 km per gateway.
Fujdiak et al. [50]		The Xirio tool that realistically takes into account a geographical radius of 10 km surrounding the gateway site under analysis.
Poluektov et al. [51]		Provided a reliable connection to cover a distance up to 6 km between an end device and a LoRaWAN gateway.
Petroni et al. [52]	Interference	A synchronization method used for canceling out interference by superposing LoRa packets

(Continues)

TABLE 4 | (Continued)

Authors	Challenges	Discussions
Hoeller et al. [53]		In the presence of IEEE 802.15.4G interference and inadequate SF orthogonality, two techniques are used to optimize LoRaWAN design.
Stoynov et al. [54]		Look out for the types of interference that arise when the efficient and interference signals utilize the same or different spreading factors (CSFI and ISFI, respectively).
Vejlgaard et al. [55]		Both LoRaWAN and Sigfox offer excellent indoor coverage of greater than 99% when there is no interference.

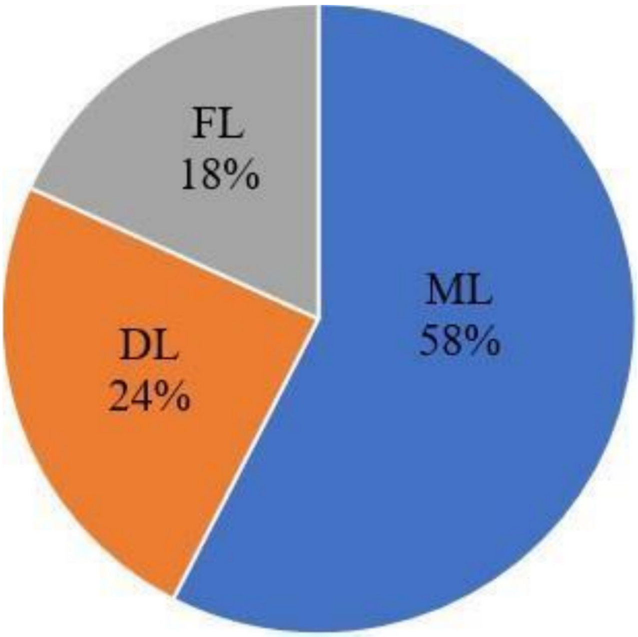

FIGURE 11 | ML/DL/FL papers in LoRaWAN.

TABLE 5 | Methodology of our research work.

Category	Papers	Description
Existing survey	26	Overviews, surveys, or factual discussions about existing technologies, methodologies, and frameworks.
Challenges	24	Challenges faced in LoRaWAN Network
ML/DL/FL	39	ML/DL/FL techniques used in the LoRaWAN network
Current solutions	6	Provides recent solutions to the LoRaWAN network
Application	16	Exploration of various applications of ML in LoRaWAN networks, demonstrating practical benefits.

were reviewed for this survey, and their categorization is presented in Table 5.

3 | ML/DL/FL Techniques

3.1 | Machine Learning

Machine learning is a branch of artificial intelligence (AI) focused on developing algorithms that enable computers to learn from data. The concept of ML was first introduced by Arthur Samuel in 1959. ML involves the scientific study of computational models and techniques that allow computers to perform tasks without explicit programming [56]. The amount of data used for training largely determines the accuracy and reliability of the prediction model. The main types of ML, as illustrated in Figure 12, are supervised learning—Models are trained using labeled data to predict outcomes for new, unseen data; unsupervised learning—Models identify hidden patterns or structures in unlabeled data; reinforcement learning—An agent learns decision-making strategies by interacting with its environment and maximizing cumulative rewards [57]. A summary of ML models applied in LoRaWAN between 2021 and 2025 is presented in Table 6.

3.2 | Deep Learning

Deep learning algorithms are a subclass of ML techniques designed to extract hierarchical feature representations through multiple layers of distributed models [73]. This emerging approach has been widely adopted in classical AI applications, as illustrated in Figure 13. The primary advantages of DL include its ability to handle complex and high-dimensional data, high accuracy when processing large datasets, and scalability, which is critical in the era of massive data generation. The common methods of DL networks are feedforward neural networks, convolutional neural networks, recurrent neural networks, and autoencoders, as shown in Figure 14. The applications of DL techniques are audio processing, speech recognition, visual data processing, and natural language processing [74]. A summary of the DL approach related to LoRaWAN is illustrated in Table 7.

3.3 | Federated Learning

Federated learning is a method of training ML models collaboratively across multiple devices without explicitly sharing the local

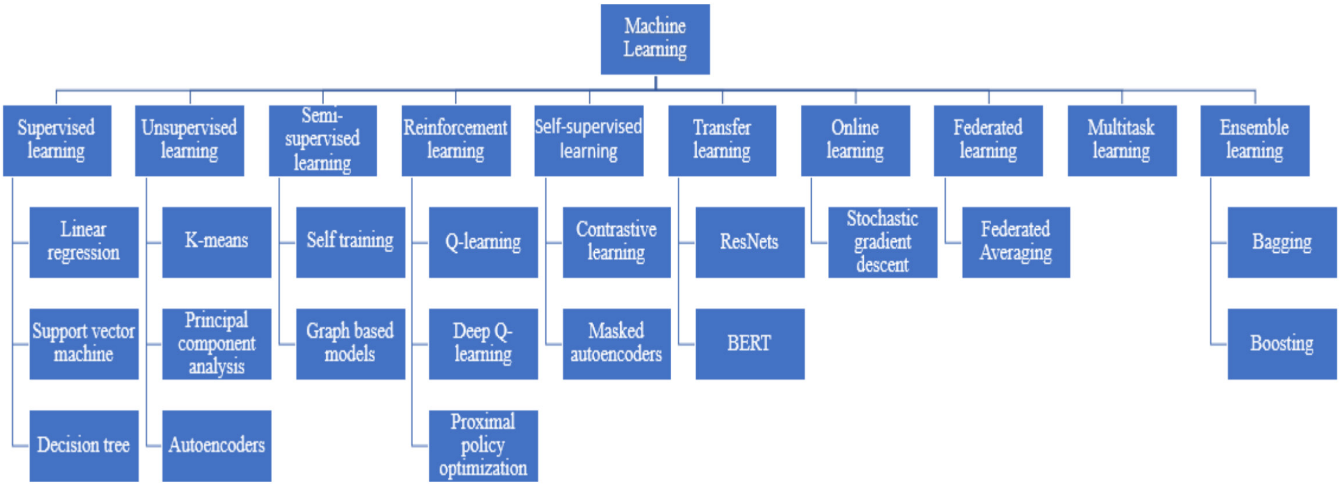

FIGURE 12 | Methods of machine learning.

data stored on each device, as illustrated in Figure 15. Instead of centralizing data to develop a model, FL allows each device to train a model locally and share only the model updates with a central server. The central server then aggregates these updates to create a global model, which is subsequently distributed back to the devices [82]. Despite its advantages in data privacy and distributed learning, FL faces several challenges, including high communication overhead, system heterogeneity, statistical data differences across devices, and privacy risks [83]. A summary of recent FL approaches applied to LoRaWAN is presented in Table 8.

Figure 16 illustrates the progression of models and techniques applied in LoRaWAN networks over the five-year period 2020–2025. Each year introduces increasingly advanced methodologies aimed at improving efficiency, scalability, and overall network performance. The evolution begins in 2020 with simpler models such as LSTM-EKF, gradually advancing to ML and DL models like SVM, CNN, and neural networks. By 2023, FL and clustering algorithms will emerge to address distributed optimization and network adaptability. 2024 showcases state-of-the-art techniques such as Bi-LSTM, Generative Adversarial Networks (GANs), and ML-based transmission power control, reflecting a shift toward intelligent and energy-efficient network solutions. In 2025, research explores Decision Trees, XGBoost, FCA-LoRa, TinyML, and hybrid FL + RL algorithms, demonstrating the continuous evolution toward smarter, highly optimized LoRaWAN deployments.

4 | Outcomes of the Latest Research

In this section, we provide an overview of the latest measurements and existing solutions to address the data packet, coverage range, energy consumption, and collision rate.

4.1 | Performance Measurements

This section highlights key performance evaluations of LoRaWAN networks enhanced with ML and DL techniques. The assessments conducted across urban, suburban, rural, and indoor environments provide valuable insights into the capabilities and limitations of ML-enhanced LoRaWAN systems. Table 9 summarizes the findings, categorized by Theoretical/Mathematical (T/M) analysis, Simulation (S), and Testbed (T) evaluations. Figure 17 illustrates the plotted structure of the performance metrics, providing a comparative visualization of network behavior under different conditions.

1. Localization Accuracy

Localization accuracy is a crucial performance metric, particularly for applications such as tracking, navigation, and environmental monitoring. Using ML techniques like RF fingerprinting and neural networks, studies like [66, 67] indicate average location errors of 12.16 meters and 6.7 meters, respectively. Notably, [80] used RSS-based models optimized by DL algorithms to achieve a 96.512% localization accuracy in indoor installations.

2. Packet Delivery Ratio/Packet Success Rate

For LoRaWAN systems, ensuring high data reliability is crucial. Packet delivery ratio (PDR) performance is generally high, ranging from 90% to over 99%, as reported in most studies. For example, [63] achieved a PDR of 91%–94% using ML-based adaptive scheduling [61], while [60] reported 95.8% using optimized SVM and Temporal Fusion Transformers. Study [64] achieved PDR > 99% through federated ML coordination across nodes. Similarly, hybrid detection and dynamic spectrum allocation techniques [60] demonstrated consistent success rates in confined indoor scenarios [72].

3. Energy Consumption and Trade-Offs

Energy efficiency is a critical factor for LoRaWAN nodes, which typically rely on battery power. Several studies have applied ML techniques for energy-aware routing, adaptive duty cycling, and transmission power control. For instance, [60, 61] reported energy savings of approximately 32.6% and 25%, respectively. Similarly, [63] employed unsupervised learning–based scheduling techniques that reduced energy consumption by 30%–35%. These findings highlight the potential of ML to optimize energy usage

TABLE 6 | Overview of ML models in LoRaWAN (2021–2025).

Role	Ref	ML models	Key contributions	Constraint
Anomaly detection	[58]	CBLOF (unsupervised)	Detects irregularities in network behavior	Computationally light, data scarcity
Traffic prediction/optimization/signal power prediction	[30, 59, 60]	AR, Firefly, SVM, Hybrid MAC model, Decision Trees, XGBoost	Predicts traffic, integrates ML in environmental monitoring	Real-time capable, needs continuous real-world data
Adaptive routing/delay optimization	[61, 62]	Adaptive scheduling, K-means clustering	Reduces delay and optimizes scheduling	Real-time capable, computationally light
Energy efficiency	[58, 63–65]	Gradient Boosting, LSTM, RF, SVR, MLR, CPLS, ML-based TPC	Reduces energy usage and predicts energy consumption	Power-aware, model generalizability
Localization	[66–68]	KNN, Neural Net, Random Forest	Node location estimation	Data scarcity
Device identification	[69]	CNN (ANN-based)	Classifies device behavior in LoRaWAN	Scalability concern
Parameter allocation/resource allocation	[70, 71]	MLP, Gaussian Regression	Allocates SF, detects greedy behavior	Model generalizability, scalability
Healthcare monitoring (Application)	[72]	K-fold cross validation	Disease prediction through data analysis	Not explicitly constrained

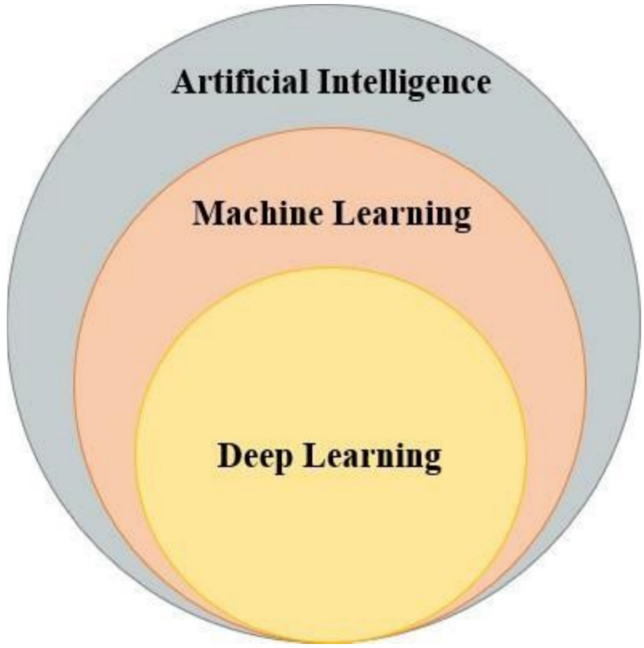

FIGURE 13 | Understanding the connection: AI, machine learning, and deep learning [21].

while maintaining network performance, enabling efficient and sustainable LoRaWAN deployments across diverse environments.

4. Collision Rate and Prediction

To enhance overall network throughput, ML techniques have been employed to predict and mitigate data collisions. For example, [61] reported a 40% reduction in collision rates using context-aware models, while [76] achieved up to 95.7% prediction accuracy in collision avoidance through pattern analysis and DL. These capabilities significantly improve system reliability, particularly in densely deployed LoRaWAN environments, where collision management is critical for maintaining high-quality network performance.

5. Coverage Range

Coverage capabilities in LoRaWAN networks are influenced by both the deployed models and environmental conditions. In urban environments, typical coverage ranges from 2 to 5 km [58], while in rural areas, it can extend up to 15 km. For indoor scenarios, evaluated performance within a 1000-m^2 area, whereas [68] achieved coverage over 30,000 m^2 using high-frequency spectrum. Hybrid systems that integrate FL and event-driven learning models, such as those proposed in [72, 79], have demonstrated efficient spectrum utilization, enabling scalable coverage even in complex or challenging terrains.

4.2 | Challenges and Limitations of ML-Based Approaches

Despite the potential of ML to enhance LoRaWAN network performance, several challenges hinder its practical deployment. A major limitation is the scarcity of diverse, publicly available

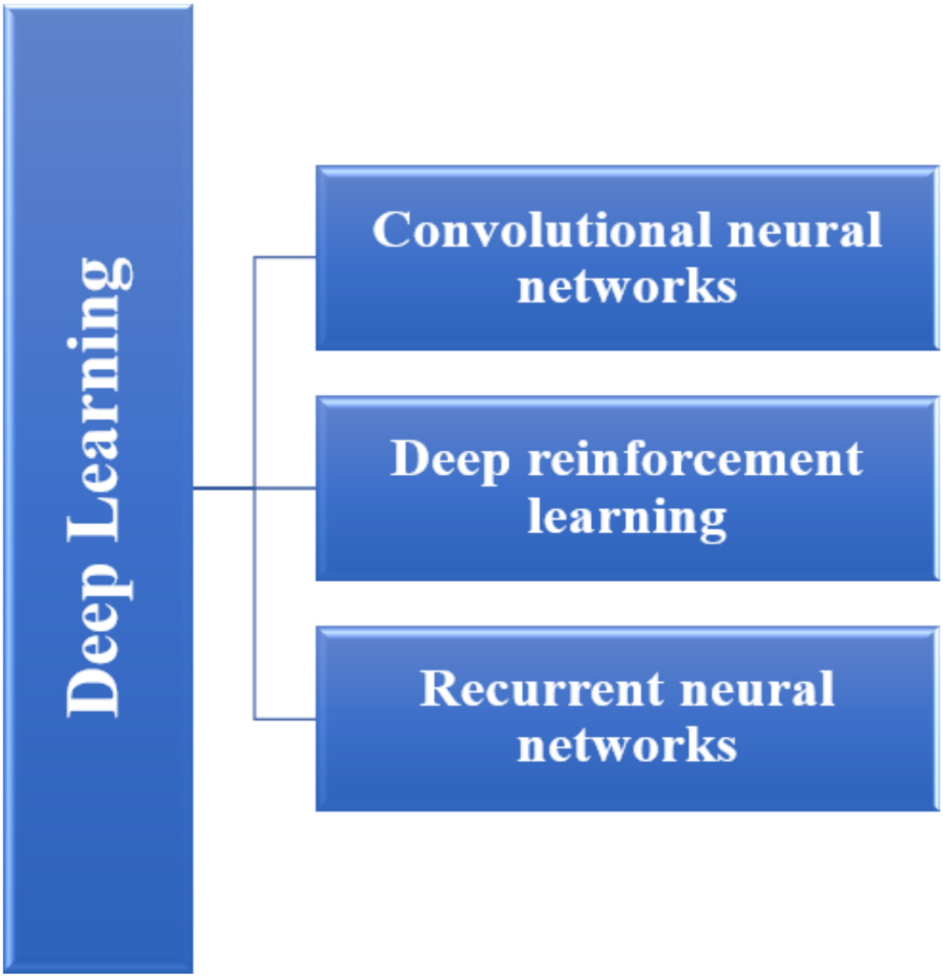

FIGURE 14 | Types of deep learning.

datasets, which restricts the development and benchmarking of robust ML models. Implementing complex ML algorithms on edge devices is also difficult because of the inherent resource constraints of LoRaWAN end nodes, such as limited memory, processing capability, and energy.

Another challenge lies in model interpretability, especially in critical applications like security or health monitoring, where understanding the reasoning behind ML decisions is crucial. Moreover, frequent data transmission between end devices and cloud platforms leads to communication overhead and latency, further reducing efficiency. Addressing these limitations is essential to enable scalable, intelligent, and practical LoRaWAN systems.

1. Limited Dataset Availability & Generalizability

Training and evaluating ML models in LoRaWAN research is challenging due to the scarcity of publicly available datasets with labeled information, such as signal measurements, interference patterns, and ADR actions. Even existing surveys highlight only a few open data sources used for resource allocation studies [26]. Furthermore, models trained in a specific deployment environment—such as rural or flat terrain—often fail to generalize to other geographic regions or hardware versions. For instance, AI-based propagation models may struggle when exposed to new channel conditions that were not represented during training [71].

2. Model Deployment on Resource-Constrained Devices

End devices (EDs) in LoRaWAN networks often face strict constraints in terms of CPU, memory, and energy. DL models, such as LSTM, typically require cloud-based processing, which can increase latency, energy consumption, and privacy risks, making them less feasible for edge deployment [90]. Lightweight models like decision trees are easier to interpret and deploy but may struggle to capture complex time-series behaviors or environmental variations. Conversely, more sophisticated models often necessitate off-device execution, which introduces challenges such as model drift, higher communication overhead, and additional operational costs.

3. Explainability and Trust in ML Decisions

Many neural network and ensemble-based models used in LoRaWAN for link-budget estimation or parameter optimization lack interpretability. This limits effective debugging, reduces operator trust, and complicates certification in regulated deployments [71]. While explainable ML techniques—such as feature importance analysis—enhance transparency, they can also expose the

TABLE 7 | Overview of DL in LoRaWAN approach (2020–2025).

Role	Ref	DL models	Key contributions	Constraint
Collision prediction	[75]	LSTM-EKF	Predicts collision rate in LoRaWAN	Resource-constrained deployment
Scalability optimization	[75]	LSTM + Autoencoder	Enhances scalability through cluster-wise model learning	Limited generalization
Spreading Factor allocation/ collision detection	[76, 77]	FCNN, CNN, k-NN, Decision Tree Classifier, Random Forest, Multinomial Logistic Regression	Allocates spreading factor and detects collisions	Low delivery ratio/performance, feature availability varies across deployments
IoT application –object detection	[78]	WPOD-NET, SVM	Detects parked vehicles using deep object detection	Limited generalization
Signal propagation modeling	[79]	Bi-LSTM	Improves the accuracy of path loss estimation for LoRa communication	Technology-specific limitation
Localization (RSS-based)	[80]	MLP + GAN	Achieves 96.5% localization accuracy	Resource-constrained deployment
Network parameter optimization (SNR, RSSI)	[31]	LSTM (DL), ANN (ML)	Achieves high predictive accuracy $R^2 = 0.999$, RMSE = 0.203	Requires continuous learning updates
Resource allocation & SF/power optimization	[81]	1D CNN, LSTM (DNN), TinyML	CNN-LSTM runs on the server to predict SF and power, TinyML enables EDs to self-adjust communication parameters	Edge device limitations addressed via TinyML; server-side models require more compute

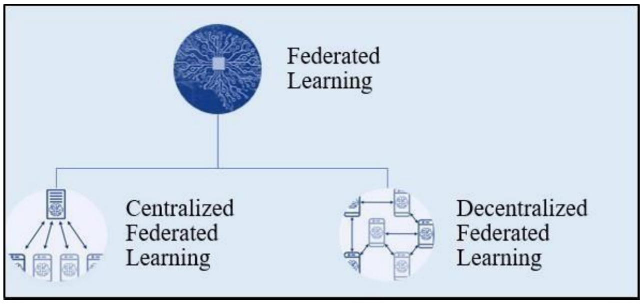

FIGURE 15 | Types of federated learning.

underlying model logic to adversarial exploitation or reverse engineering, introducing potential privacy and security risks.

4. Scalability, Congestion and Interference

LoRaWAN deployments in urban or large-scale environments often suffer from high collision rates and spectrum interference. ML models are expected to dynamically optimize SF, transmission power, and channel allocation; however, coordinating these adjustments across multiple nodes in real time remains challenging. Moreover, the energy demand of ML-driven resource management can conflict with the battery-constrained design of LoRaWAN nodes. A key unresolved challenge is achieving energy-efficient ML execution while maintaining the required communication quality of service [91].

4.3 | LoRaWAN Current Solutions

In this section, we address key challenges in LoRaWAN networking and present practical solutions based on current research studies. Comprehensive analyses have been conducted to resolve specific issues impacting LoRaWAN performance. For clarity, the reviewed studies are categorized into five groups according to their primary focus areas.

i. Energy Usage

PLoRa [92] modifies ambient LoRa signals and reroutes them to alternate channels, enabling remote communication between battery-free IoT devices. It integrates lightweight algorithms with low-power hardware to achieve efficient backscatter communication. According to [93], PLoRa represents the first wide-area backscatter system, enabling long-range, small-scale communication with standard LoRa devices. It is capable of operating in diverse environments, achieving coverage distances of up to 2.8 km, and utilizes an ultralow-power LoRa backscatter IC that consumes only 9.25 μW.

> **Significant insights**: PLoRa allows LoRaWAN systems to support battery-free IoT devices, thereby reducing both network management complexity and energy consumption. Its system architecture enables low-power backscatter devices to communicate seamlessly with existing LoRa nodes, improving network reliability and flexibility [92]. The backscatter-based design significantly reduces power requirements compared to conventional LoRa chipsets, resulting in substantially lower energy usage within LoRaWAN networks [93].

ii. Range of Coverage

Study [94] proposes a novel approach for assessing LoRaWAN coverage in a smart campus environment. It introduces a mapping-based survey method for coverage evaluation along with the design of a mobile node. Rather than focusing on a specific LoRaWAN deployment, the proposed method is validated through a practical application scenario, demonstrating its effectiveness in real-world testing. Similarly, study [95] investigates LoRaWAN radio propagation in the 868 MHz band through comprehensive measurements conducted in suburban and rural areas of Lebanon. Path-loss (PL) models were developed from empirical data and compared with existing models, highlighting the accuracy and practicality of the proposed models. The experiments achieved coverage up to 8 km in urban areas and up to 45 km in rural regions.

> **Significant insights:** This research provides a systematic method for mapping and analyzing LoRaWAN coverage, which is particularly useful for large-scale deployments [94]. It also demonstrates strategies to optimize LoRaWAN coverage and performance by developing reliable path-loss (PL) models, highlighting how long-range communication is achievable with LoRaWAN, especially in rural environments [95].

iii. Correction of Errors

Study [96] identifies significant frame loss in LoRaWAN networks, particularly at greater distances from gateways, based on an analysis of temporal and geographical network characteristics. To address this issue, an innovative coding technique called DaRe is proposed, which enhances data extraction by embedding redundant information into transmission frames, thereby reducing data loss. Furthermore, study [97] introduces a distributed coding approach that enables an adaptive wireless protocol for backscatter devices, allowing up to 256 units to transmit simultaneously. This method effectively addresses challenges such as synchronization and the near-far problem by decoding all signals using a single FFT operation.

> **Significant insights:** Data recovery in scenarios with significant frame loss can be substantially improved through hybrid techniques such as DaRe, which combines convolutional and fountain codes [96]. Additionally, employing distributed coding methods, as implemented in scalable backscatter systems, enhances error correction by enabling the decoding of multiple simultaneous transmissions, including those occurring below the noise floor [97].

4.4 | LoRaWAN Simulation Tools

A computational model is a design that incorporates computational techniques, both physical and scientific concepts, and technical formulae to describe a system's real-world instance reports. Modeling LoRa networks is crucial, as it enables the design and evaluation of LoRa-based applications without incurring significant costs before the actual system deployment. LoRa technology provides specialized and openly accessible software for simulation efforts [11]. The various simulation tools and their features are described in Table 10.

TABLE 8 | FL survey from 2023 and 2025.

Role	Ref	FL models	Key contributions	Constraint
Bandwidth & Energy Optimization	[84]	FL over LoRa Mesh Network	Demonstrates the feasibility of on-device FL training; explores trade-offs between speed and bandwidth.	Training–accuracy trade-off; bandwidth overhead
Imperfect Data Handling (Classification)	[85]	FL for Transportation System	Handles noisy/imperfect labeled data in LoRa-based transport systems	High energy use during training and communication
Privacy-Preserving Communication	[86]	FL-LoRaMAC	Maintains data confidentiality in IoT environments through FL integration	Not compatible with legacy LoRaWAN unidirectional architecture
Anomaly Detection in IIoT	[87]	Neural & Nonneural FL	Detects industrial anomalies using FL while maintaining data privacy	Excessive epochs can overload constrained LoRa devices
Environmental Monitoring in Remote Areas	[32]	FL, Aerial FL	Proposes an integrated system combining AAN, FL, and hybrid LoRa P2P/LoRaWAN for remote environmental monitoring	Challenges in aerial deployment, FL coordination
Edge Intelligence for IoT	[88]	Hierarchical Federated Learning (FL), Knowledge Distillation (KD), FCA-LoRa (custom MAC)	Combining FL, KD, and MAC for energy-efficient, privacy-preserving learning; validated in smart agriculture and livestock farming scenarios.	Strict duty cycle, bandwidth, and energy constraints in LoRaWAN
Secure and Energy-Efficient Routing Optimization	[89]	FL, Reinforcement Learning (RL)	FL + RL framework for multihop routing in LoRaWAN; integrates energy awareness, trust, and real-time link quality	Multihop routing complexity

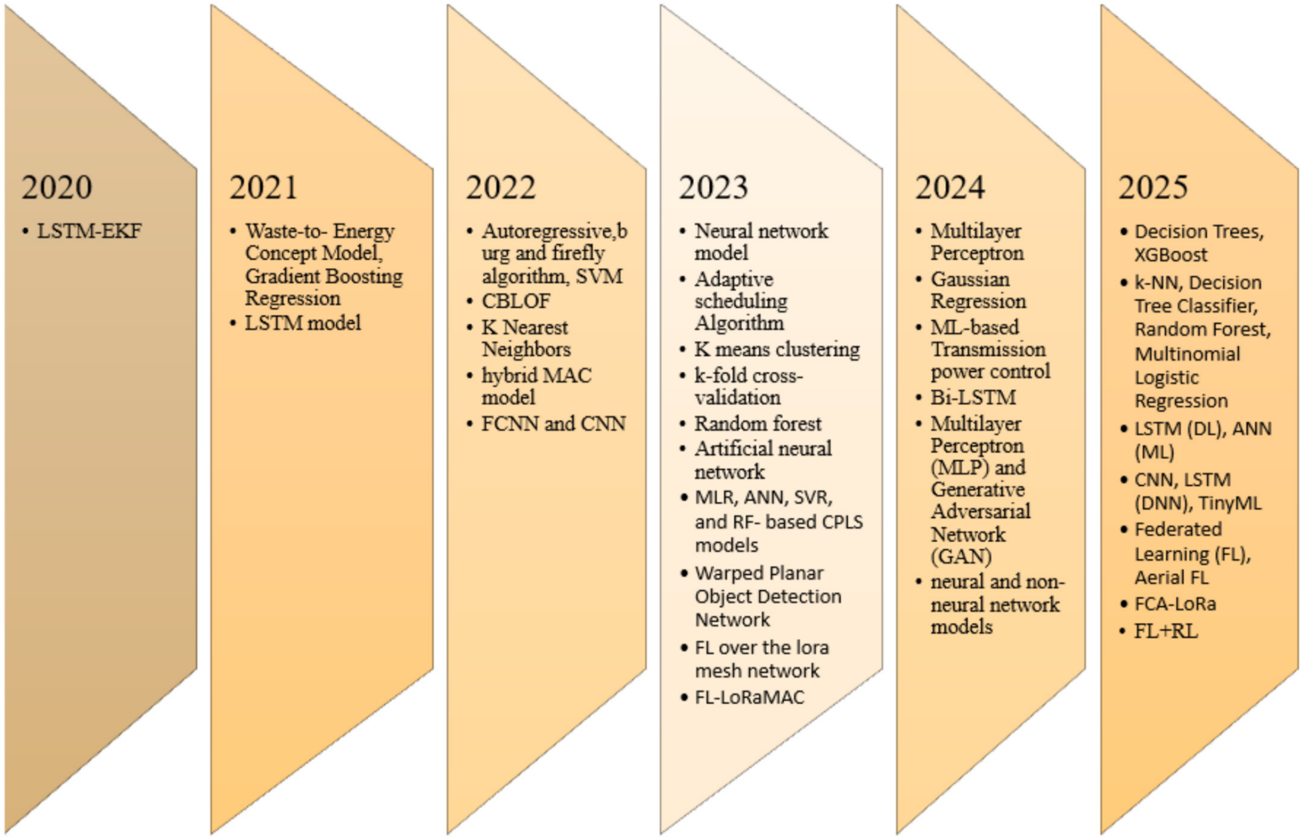

FIGURE 16 | Approached models in LoRaWAN from 2020 to 2025.

5 | Application

This section explores the diverse application areas of LoRaWAN, highlighting how the technology addresses specific challenges and enables innovative solutions. LoRaWAN's ability to connect a large number of devices with minimal energy consumption has driven its widespread adoption across industries such as environmental monitoring, air quality monitoring, healthcare, agriculture, and industrial automation, as illustrated in Figure 18. Its robust and flexible network architecture supports a wide spectrum of applications, transforming the way we manage resources, monitor environments, and optimize operations in both urban and rural settings.

1. Environmental Monitoring

The ability to deploy sensors in remote locations with long battery life makes LoRaWAN particularly suitable for environmental monitoring. Typical applications include weather stations, wildlife tracking, soil moisture monitoring, and forest fire detection, all of which provide critical data for scientific research and conservation efforts. Kadir et al. [98] demonstrated the development and deployment of LoRa-based sensors to address challenges caused by forest and land fires in Riau Province, where an authentic IPv6-over-LoRa implementation was developed and evaluated. Wang et al. [33] showed that LoRaWAN can connect numerous sensor nodes to provide wide coverage, enabling environmental monitoring in IoT applications. In their approach, statistical analysis and clustering methods (e.g., K-means) were applied to detect anomalies in temperature, soil moisture, and radiation data. Additionally, Manzano et al. [99] developed Waste Radiation Monitoring (W-MON), an automated radiological tracking system for waste containers, utilizing a network of ultralow-power gamma-ray sensors functioning as LoRa transceivers. These end devices collect radiation data and transmit it to the LoRaWAN network server, supporting real-time environmental monitoring.

2. Air Quality Monitoring

LoRaWAN plays a key role in transforming metropolitan areas into smart cities. Applications such as smart lighting, waste management, and smart parking improve public services while reducing operational costs. Air quality monitoring and water management systems further contribute to healthier and more resilient urban environments. Basford et al. [100] demonstrated LoRaWAN's suitability for city-scale air quality monitoring, achieving 99% message delivery within 10 s. Thu et al. [101] deployed affordable sensors to measure temperature, humidity, dust, and carbon dioxide levels, while leveraging ML models such as ARIMA to predict air quality trends in Yangon. Jabbar et al. [102] measured 11 environmental parameters using a LoRa-based sensing system and developed a dashboard and GUI that allowed users to visualize air pollution data directly on their smartphones.

TABLE 9 | Performance measurement by ML and DL.

Ref	Evaluation method	Localization/accuracy	Data packet (PDR/PSR)	Energy consumption/ trade off	Collision rate/prediction	Coverage range
[58]	T	Not considered	**Urban:** ~88–91% transmission success **Suburban:** ~94% **Rural:** ~97%	Not considered	Not considered	**Urban:** 2–5 km **Rural:** up to 15 km
[63]	S&T	Not considered	**PDR:** ~91–94%	~30%–35% energy savings	Not considered	**Suburban: ~3 km**
[66]	T	**Location accuracy:** ~12.16 m	Not considered	Not considered	Not considered	**Urban: ~8 km**
[60]	S	Not considered	**PDR: ~95.8%**	**Energy reduction up to 32.6%**	Reduced (no numeric % reported)	Implied ~2–3 km
[67]	T	**Mean error:** ~6.7 m	Not considered	Not considered	Not considered	**Test environment area:** Indoor **~1000 m^2**
[61]	S	Not considered	**PDR:** Up to **96.8%**	Energy saving of ~25%	**Collision reduction by ~40%**	~2.5–3.5 km
[72]	S	Not considered	High success rate (600 + packets to 20 nodes in 30 min)	HEADR reduces energy	Reduced via HEADR switching and dynamic range allocation	High coverage: Uses 24–54 GHz spectrum
[68]	S&T	**~50% better accuracy**.	98.7% of transmitted packets	Not considered	Not considered	Coverage: **30,000 m^2**
[64]	S&T	Not considered	PDR ≥ 99%	**~20% energy saving than ADR model**	Not considered	ENs positioned at **2.1 km, 3.4 km, 6.1 km, and 8.3 km** from the gateway (GW).
[75]	T/M & S	Not considered	Not considered	Not considered	**MSE:** as low as 0.936×10^{-3} R^2 (coefficient of determination): up to 0.98435	Not considered
[75]	S	Not considered	Coverage probability improved up to **0.65**	Not considered	Not considered	54 sensor nodes within a **40 × 30 m indoor space**
[76]	S	Not considered	**Highest PDR** achieved	Not considered	Prediction accuracy: up to **95.7%**	Network radius: **3000, 5000, and 7000 m**
[79]	S&T	Not considered	PDR > 90%	Not considered	Not considered	**4 × 4 km** mountainous area
[80]	S	**Highest localization accuracy achieved: 96.512%**	Not considered	Not considered	Not considered	Not considered

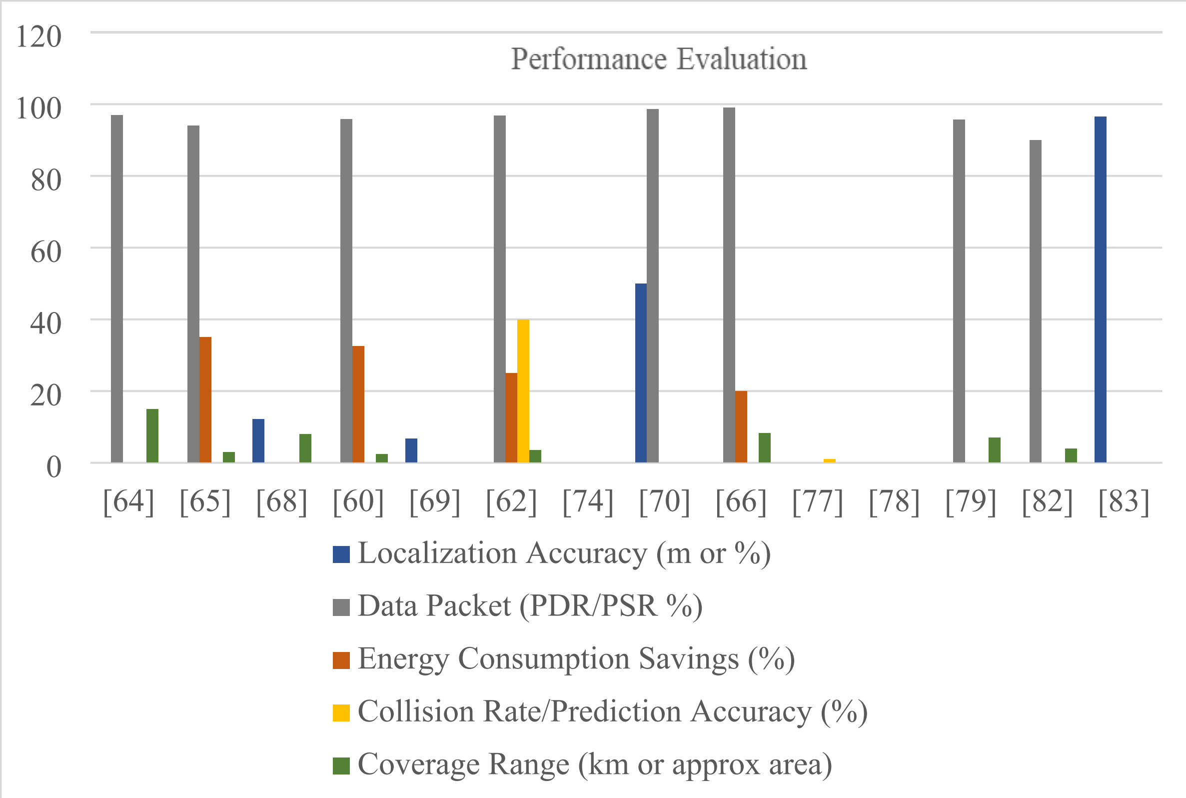

FIGURE 17 | Performance evaluation metrics.

TABLE 10 | Various simulation tools used by LoRaWAN network.

Simulation tool	Platform	Key features	Pros	Cons
NS-3	Open-source	Detailed network simulation, customizable MAC/PHY layers	Comprehensive, highly customizable, and extensive community support	Steep learning curve, complex setup
OMNeT++	Open-source	Modular architecture, customizable, supports multiple network types	High flexibility, strong visualization capabilities	Requires significant programming effort
LoRaSim	Open-source (Python)	Models large-scale LoRa networks, focus on scalability	Easy to use, suitable for large network simulations	Limited to LoRa-specific simulations, less flexible
Cooja (Contiki OS)	Open-source	Simulates IoT networks, supports various IoT protocols	Good for low-power IoT simulations, integrates with Contiki	Limited to Contiki-supported protocols
FLoRa	OMNeT++ Framework	LoRaWAN-A specific module, a detailed MAC layer simulation	High accuracy for LoRaWAN-specific scenarios	Dependent on OMNeT++, learning curve
MATLAB	Proprietary	Simulink models for LoRaWAN, extensive analysis tools	Powerful analysis and visualization, strong support	Costly, may require additional toolboxes for full functionality
ns2 (with LoRa extensions)	Open-source	Basic network simulation, extended for LoRaWAN	Lightweight, well-documented	Older tool, less support for modern features

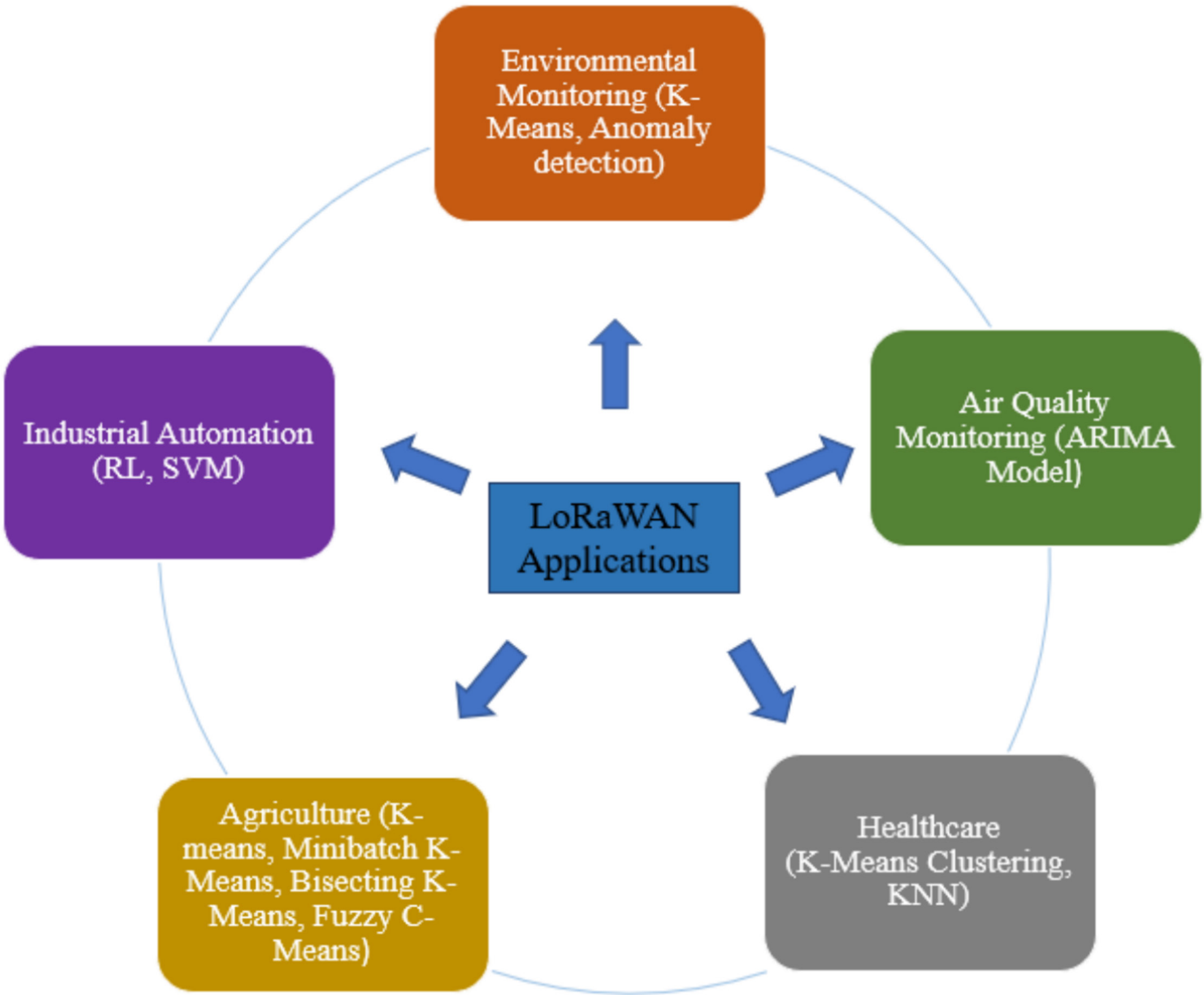

FIGURE 18 | Applications of LoRaWAN in various domains.

3. Healthcare

Mdhaffar et al. [103] presented that collected data is sent to the analysis module through the LoRaWAN network for monitoring the patient. The region covered by the network is 33 km^2 and the Gateway is put outside at a height of 12 m. The outcomes show that our system for tracking consumes at least 10 times less electricity than other systems. Taleb et al. [104] suggested TOPSIS, a method used to determine the most efficient SF depending on the health of the patient. The selection strategy minimizes error rates, particularly among patients who have a high critical level. Fernandes et al. [105] investigated the use of LoRaWAN networks for indoor and outdoor localization solutions to assist elderly individuals. The system enables them to request help during emergencies and notify remotely connected caregivers in case of accidents, achieving an average indoor transmission delay of 700 ms. Gondalia et al. [106] developed a real-time soldier health and position monitoring system using Wireless Body Area Sensor Networks (WBASNs) integrated with GPS, where K-means clustering was applied for predictive analysis. Similarly, Hossain et al. [107] proposed a human movement recognition system using LoRaWAN sensors combined with accelerometer data, with classification performed using K-nearest neighbors (KNN) and linear discriminant analysis (LDA) algorithms.

4. Agriculture

Arshad et al. [108] proposed a Smart Decision Support System (DSS) for agriculture that utilizes continuous field monitoring to optimize crop yield and sustainability by increasing per-acre productivity and reducing water seepage losses. The system integrates smart irrigation, automated control, and intelligent decision making, leveraging real-time field data to enhance resource efficiency. Valente et al. [109] deployed three types of sensors in an agricultural field, using a LoRaWAN network to transmit data between them. The results demonstrated that the network maintained continuous communication without any data loss, validating LoRaWAN's reliability for precision agriculture. Correia et al. [110] presented a methodology for determining the optimal number and placement of LoRaWAN gateways to cover large agricultural areas. The gateways were deployed using four clustering techniques, and performance metrics were evaluated to assist both system architects and end users in selecting the most efficient deployment strategy.

5. Industrial Automation

Sherazi et al. [111] investigated the functionality of LoRa radios for manufacturing automation in both conventional and energy-harvesting (EH) industrial environments. A key outcome of this research was the cost–benefit analysis comparing battery replacement costs with damage penalties across different sensing intervals. The study also reported annual CO_2 emission reductions of up to 3 kg/kWh per node. Zorbas et al. [112] proposed TS-LoRa, a mechanism that enables nodes to autonomously and efficiently determine their appropriate time slot within the network framework. TS-LoRa demonstrated reduced energy consumption while improving network efficiency. Bonafini et al. [113] demonstrated the integration of GPS and UWB-RTLS devices for spontaneous synchronization of TDMA-based medium access in Industrial IoT (IIoT) wireless networks. Using time-referenced UWB pulses, the system achieved a maximum jitter of 3.3 μs with a standard deviation of 0.7 μs, ensuring precise synchronization for industrial applications.

6 | Conclusions and Future Work

6.1 | Conclusions

LoRaWAN is a promising Internet of Things (IoT) protocol known for its long-range communication and extremely low power consumption, making it well-suited for wide-ranging IoT deployments. However, optimizing LoRaWAN networks poses several challenges due to limited bandwidth, coverage area, interference, and energy constraints of end devices. To address these challenges, ML and DL techniques have emerged as effective solutions. ML can be leveraged to improve various aspects of LoRaWAN performance, including resource allocation, SF optimization, localization, and energy efficiency. This survey presents an in-depth analysis of state-of-the-art applications of ML, DL, and FL techniques aimed at enhancing LoRaWAN network performance. The study discusses key network performance metrics and how ML models have been applied to improve these aspects. Additionally, the paper reviews the simulation tools commonly used for modeling and evaluating LoRaWAN networks and analyzes recent ML-based solutions based on their efficiency, scalability, and adaptability. Furthermore, the study highlights various practical applications of ML in LoRaWAN networks, demonstrating their relevance in solving real-world networking challenges.

6.2 | Future Recommendations

Future studies should focus on a few potential directions for bridging the gap between theoretical developments and real-world implementation. To evaluate the robustness of ML models under dynamic and unpredictable conditions such as urban mobility, interference, and hardware heterogeneity, real-world implementations in operational LoRaWAN environments are essential. Furthermore, adapting ML algorithms to other LPWAN standards, including NB-IoT, Sigfox, and Wi-SUN, can promote model generalization and extend the benefits of intelligent network management across heterogeneous IoT infrastructures. In addition, there is a growing need to develop more scalable and lightweight ML models capable of operating on edge devices with constrained computational resources. TinyML, attention-based models with fewer parameters, and distributed FL should be investigated to reduce latency and energy consumption.

In large-scale deployments, the development of hybrid ML-heuristic techniques and cross-layer AI frameworks can further facilitate self-healing, interference reduction, and predictive maintenance. Finally, integrating ML with emerging paradigms such as edge computing for real-time inference and blockchain for secure data sharing opens new avenues for future research. Self-adaptive networks that dynamically reconfigure themselves in response to node behavior and environmental context can be powered by RL and hierarchical actor-critic frameworks. Looking ahead, synergies between LoRaWAN and future 6G infrastructures are anticipated to unlock ultra-reliable, low-latency, and intelligent IoT networks on a global scale.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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