

# A Systematic Literature Review on Machine Learning Methods for Improving LoRaWAN Performance

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**ABSTRACT** - The growing deployment of the Internet of Things (IoT) devices makes the existing LoRaWAN networks increasingly prone to performance degradation under crowded networking conditions. To ensure sustainable development of LoRaWAN technology, new strategies to optimize power consumption, enhance network scalability, and alleviate congestion need to be designed. The integration of Machine Learning (ML) technologies into LoRaWAN architecture is expected to be a key solution to addressing critical infrastructure challenges. The objective of this study is to conduct a systematic literature review of the evolution of ML-enhanced LoRaWAN networks following to PRISMA 2020 guidelines. This review paper discusses four research questions: ML approaches applied, KPIs addressed, real-world applications of ML-based LoRaWAN networks, and knowledge gaps in the area. Analysis is conducted based on 70 scholarly papers published between 2020 and 2025. The review identifies prevalent ML approaches, such as supervised learning, unsupervised learning, and reinforcement learning, and explores their influence on various KPIs, including data rate, latency, PDR, and others. Instead of relying on the cloud, ML applications in LoRaWAN networks are moving toward edge computing. Minimizing backhaul traffic resulting from ML algorithms is run at the gateway and end-device levels. Precision agriculture and smart urban infrastructure are where ML algorithms significantly enhance monitoring capabilities. Access to standardized datasets remains limited, making validation of ML algorithms a challenge at the same time. The strategic framework proposed for future research is moving away from centralized, cloud-centric processing toward intelligent, hybrid edge-cloud architectures.

## 1. INTRODUCTION

The Fourth Industrial Revolution (IR 4.0), characterized by a new productivity paradigm powered by cyber-physical systems and hyperconnectivity, is bringing about significant changes in the world of industrial processes. The Internet of Things (IoT), a huge interconnected network of gadgets capable of sensing information and communicating it automatically without any human intervention, is considered to be the main feature of IR 4.0. There are a wide variety of IoT applications in industries ranging from healthcare to smart city, but Industrial Internet of Things (IIoT) is the biggest innovation within the concept. IIoT concentrates on crucial scenarios requiring flawless precision, such as large-

scale farming or smart manufacturing, hence Low-Power Wide-Area Networks (LPWAN) technologies are being increasingly adopted by these sectors.

As more and more IoT devices are deployed into operation, LoRaWAN networks are becoming highly vulnerable to performance degradation due to crowded networking conditions. To ensure sustainable development of LoRaWAN technologies, novel strategies need to be developed to tackle problems with power efficiency, network scaling, and congestion. The adoption of machine learning (ML) technologies appears to be a promising direction in solving infrastructural challenges. The goal of the current study is to carry out systematic review of the history of ML-enhanced LoRaWAN according to the PRISMA 2020 guidelines. Four research questions will be considered in this paper, concerning approaches used to integrate ML, key performance indicators, real-life applications, and current knowledge gaps. The analysis is based on 70 scholarly sources from 2020 to 2025. The review will cover popular ML approaches, such as supervised learning, unsupervised learning, and reinforcement learning. Furthermore, their effect on LoRaWAN parameters like data rate, latency, Packet Delivery Rate (PDR), etc. will be considered. It is also important to note that currently the use of ML algorithms on the cloud is shifting towards edge. In other words, ML techniques will be executed on the gateway and end-device levels, thereby reducing backhaul load. Applications of ML in LoRaWAN can be mainly observed in smart urban infrastructures and precision agriculture, where algorithms enhance IoT capabilities. On the other hand, access to open datasets is limited, making testing of ML algorithms problematic. The strategic framework for further investigation should imply a transition from centralization to edge-cloud intelligent architecture.

Because of its unique ability to provide extended-range communication at low power consumption costs, LoRaWAN (Long Range Wide Area Network) protocol is emerging as the best choice among LPWAN technologies making it ideal for remote IIoT deployments. Although LoRaWAN is a great choice when it comes to transmitting data, the massive amount of data collected by IIoT sensors requires additional intelligence. Machine learning (ML) algorithms have been incorporated in order to enable cognitive functions and predictive analytics. According to recent publications, ML, together with LoRaWAN technologies, is essential in order to create IoT solutions capable of instant response to changes in the environment (Kumar & Dewang, 2025; Saxena et al., 2025).

## 2. RELATED WORK

Even though the state-of-the-art in LoRaWAN performance and IoT optimization has been reviewed in numerous articles, the majority of current research considers LoRaWAN connectivity and Machine Learning (ML) analytics to be two separate domains. While traditional reviews of LoRaWAN do not cover sophisticated machine learning algorithms in conjunction with LoRaWAN, the current SLR will present the latest innovations that have emerged over the past five years (from 2020 to 2025). The purpose of the current systematic review of the literature is to map out popular ML approaches utilized in LoRaWAN solutions and highlight how they affect Key Performance Indicators (KPIs) of these systems. Another distinguishing characteristic is the consideration of Edge AI and network self-adaptation as major trends.

### i. ML Integration at the Device Level (End Node/Edge)

At the device level, the objective of integrating machine learning with the focus on TinyML is to make smart functionality available at the place where the data is produced, even on hardware with strict resource constraints. The idea is to reduce latency and conserve energy by conducting processing operations locally. According to Zaidi et al., (2022), TinyML can be implemented on end nodes for smart agriculture, reducing memory requirements while maintaining high performance. TinyML can operate on end nodes used in smart farming without compromising performance while reducing the amount of memory required. In another study, Sabovic et al., (2023) demonstrate that TinyML and CNNs are possible on battery-less IoT devices; therefore, sophisticated data can be processed locally without being supplied with power. In the same way, Alwaisi et al., (2024) combine TinyML with different algorithms such as Random Forest and K-Nearest Neighbors to handle latency in digital health monitors. All these findings point out that the trend is the

emergence of "on-device intelligence" where machine learning models are designed to perform on LoRa end nodes to respond promptly and consume less power.

Figure 1 presents the flowchart of how the process works. The data is transferred via WiFi to the HELTEC LoRa Wireless Stick acting as the gateway. In the case study, a NodeMCU (ESP8266) IoT device is used in connection with an IMU sensor (MPU-6050). The gateway is configured with customized firmware that comprises the device manager and a light-weight React-based web server providing the ability to use two types of connections: WiFi and LoRa. (Zaidi et al., 2022).

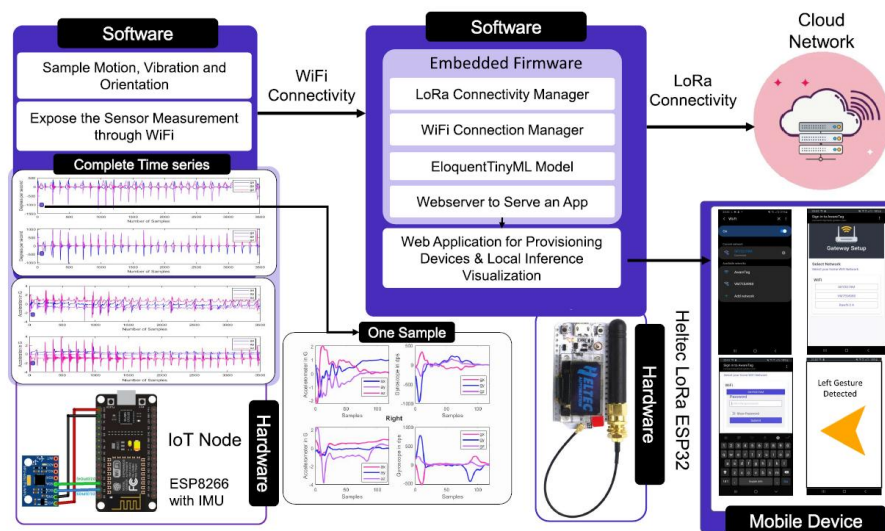
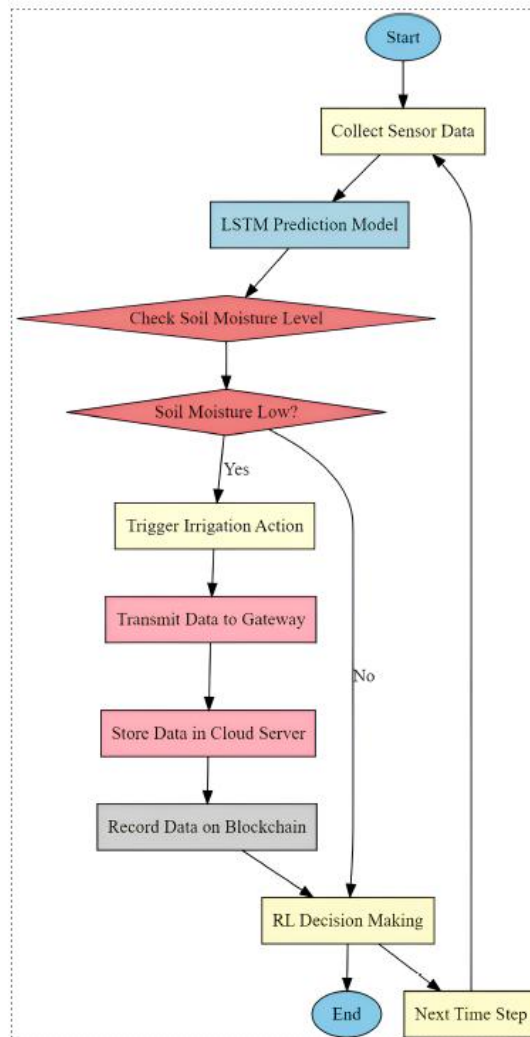


Figure 1: Tiny-ML setup (Zaidi et al., 2022)

## ii. ML Integration at the Gateway Level (Edge Computing)

Placing the ML model in edge computing, which operates at the gateway level, proves to be an important connector facilitating the improvement of network management and data processing capabilities. For example, the application of a Fuzzy Support Vector Machine (FSVM) model in a LoRaWAN gateway by Wang et al., (2022) helps to reduce power consumption and manage collisions. Additionally, Atan et al., (2023) emphasize Deep Neural Network (DNN) implementation in edge networks, which leads to reduced latency in data processing and improved performance in time-critical applications. Further, in order to increase the accuracy of predictive analytics in the area of smart agriculture, Munaganuri et al., (2025) suggest using LSTM models at the gateway. Overall, combining cloud processing and local device limitations through ML at the gateway level provides a flexible solution suitable for IIoT real-time tasks.

In the article by Munaganuri et al., (2025), one can observe the proposed technical framework illustrated by their Figure 2. In particular, the suggested approach starts from the Perception Layer that gathers real-time data from the environment with sensors. It is transmitted to the network server with the help of LoRaWAN gateways. LSTM-based data processing analyzes not only the current but also historical data to provide prediction regarding soil moisture content. It is the point of integration. Only after that the results of ML inference, along with sensor logs, are sent to a mobile/web application for the end-user to review them. However, before reaching the end-user, these are saved in Blockchain due to smart contracts.

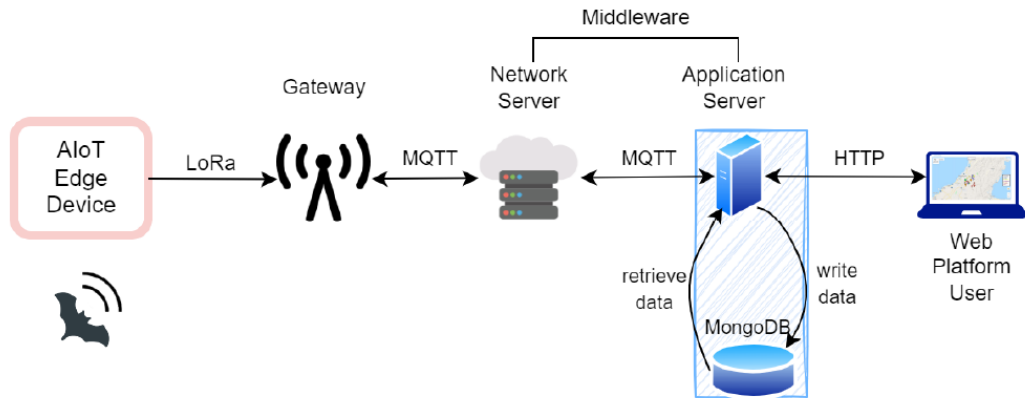


**Figure 2:** Model architecture for ML-Gateway integration (Munaganuri et al., 2025)

### iii. ML Integration at the Cloud/Network Server Level

By using high-performance computing resources, machine learning is integrated into cloud and network servers to process detailed data and generate long-term analytical insights. Pan (2025) shows that cloud-based Deep Learning works well in healthcare applications, as centralized processing improves the sensitivity and accuracy of patient monitoring. The combining of cloud platforms for biodiversity monitoring is also covered by Mahbub et al., (2024) who use Convolutional Neural Networks (CNNs) to examine vast amounts of environmental data transmitted via LoRaWAN networks. According to research, the cloud remains the best option for compute-intensive jobs and Big Data analytics that require data collection across many geographic areas, even though it introduces more latency than the edge.

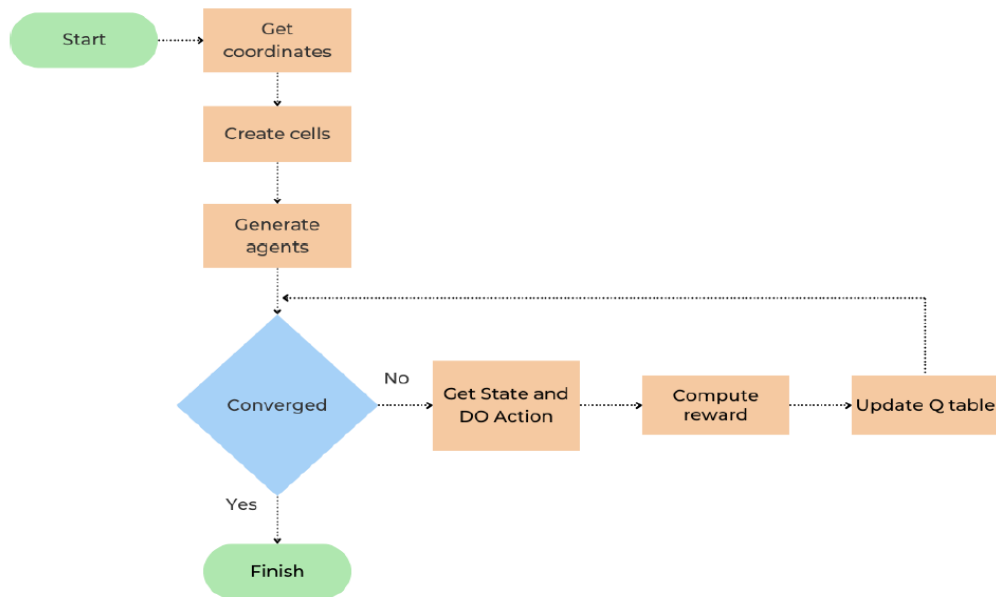
The network architecture and data flow of the system when a bat event is detected are depicted in Figure 3 from Mahbub's (2024) research. The Application Server (AS) and Network Server (NS) function as crucial middleware in this configuration, controlling the collection, archiving, and availability of data from edge-side devices. AS acts as the backbone of the website, handling the transaction of databases not only for the queries generated by the user but also for the real-time logs detected through HTTP protocol. On the other hand, NS uses The Things Network (TTN).



**Figure 3:** System's network architecture and data flow from the paper (Mahbub et al., 2024)

#### iv. Hybrid Edge-Cloud Architecture

In transitioning to a hybrid edge-cloud computing framework, there can be an integrated LoRaWAN network management architecture that includes both local and cloud computations. As explained by Sathupadi et al., (2024), there are two key advantages of adopting such a hybrid architecture in terms of cloud computing being used for storing data over a long time and local processing of any instant requirements. The traditional approach of employing centralized clouds only does not provide enough energy savings and efficiency compared to the cooperative method adopted by the hybrid approach. As a way to increase scalability in LoRaWAN, the adoption of Reinforcement Learning techniques through Q-learning is recommended by Alhattab et al., (2025) This advanced integration of intelligence increases flexibility in growing LoRaWAN networks. An elaborate visualization of sensor-node management in an effective way is presented in Fig. 4, where the network space is divided geographically into cells and sectors (Alhattab et al., 2025) Given that sensors nodes operate at different locations from the gateways, they choose appropriate communication channels and Spreading Factors (SF). In implementing parallel Q-learning across all agents, a unique and exclusive TDMA time slot for each sensor node can be achieved.



**Figure 4:** Flowchart of TL-TS protocol (Alhattab et al., 2025)

### 3. PROBLEM STATEMENT

Despite LoRaWAN's technical benefits, scaling the protocol for complex IIoT contexts presents some inherent problems, especially with regard to network congestion, collisions, and energy depletion under high loads. Because industrial radio settings are dynamic and unpredictable, traditional LoRaWAN designs frequently rely on static characteristics. Even though machine learning is a viable way to optimize key parameters, such transmission power (TP) and spreading factor (SF), existing research is still very dispersed. While ML specialists frequently create models in isolation without taking into account the stringent computational and energy limits of LoRa-based end devices, several studies assume LoRaWAN as a "blind" pipe for data (Hammouti et al., 2024).

Additionally, there isn't a single framework that classifies which machine learning algorithms are most appropriate for particular LoRaWAN problems, like adaptive link management or security intrusion detection. There is a systematic knowledge gap about the cross-layer integration of machine learning inside the LoRaWAN stack because the existing literature frequently concentrates on specialized applications. It is challenging for researchers to determine whether machine learning architectures in LPWANs provide the optimum balance between accuracy and energy efficiency in the absence of a Systematic Literature Review (SLR) (Delgado-Rajó & Travieso-Gonzalez, 2025). By combining the available data, this SLR seeks to close this gap and offer a path for next intelligent LoRaWAN implementations.

### 4. METHODOLOGY

This study uses a structured systematic literature review (SLR) approach to guarantee that the chosen articles are thoroughly assessed in accordance with the four established research questions. This section describes a thorough process for locating, evaluating, and qualifying, with a particular emphasis on integrating Machine Learning (ML) techniques to improve LoRaWAN performance. The methodology starts with a methodical search throughout the three main databases which is Scopus, ScienceDirect, and SpringerLink by using the PRISMA 2020 framework. High-quality empirical papers are then filtered through a rigorous quality review. After that, the approach enters a phase of technical and thematic analysis to link machine learning algorithms to application sectors and performance measures. This methodical methodology offers a strong basis for combining recent research findings, pointing out important gaps, and suggesting a course of action for upcoming autonomous and energy-efficient LoRaWAN deployments.

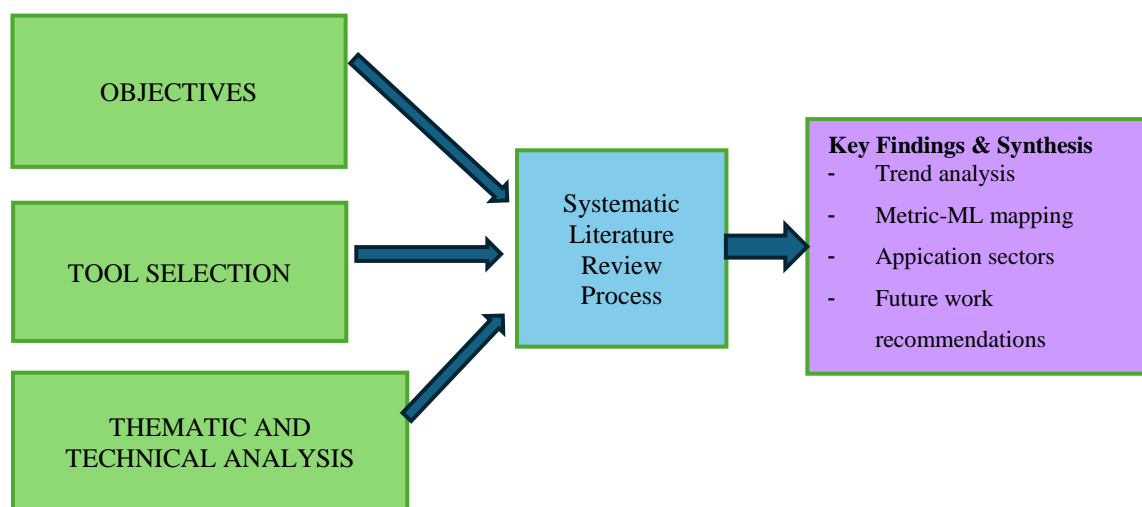
#### 4.1 Review Protocol

The PRISMA 2020 framework is used in this study to guarantee a systematic literature review (SLR) procedure that is clear and methodical. The process began with the formulation of particular research questions, which were then followed by an initial search to confirm the novelty of the study in comparison to previous works. To find pertinent material, a methodical four step selection procedure identification, screening, eligibility and including was then carried out. A quality assessment was conducted on the collected publications to confirm their relevance to LoRaWAN and machine learning integration in order to guarantee academic rigor. The chosen studies were then subjected to data abstraction and theme analysis in order to summarize the main conclusions and suggest future lines of inquiry.

#### 4.2 Formulation of Research Questions

The study analyzes current publications indexed in Springer and Scopus from 2018 to 2025 in accordance with the PRISMA 2020 recommendations for systematic literature reviews in order to accomplish this goal. From the Figure 5, the study employs a structured conceptual framework that synchronizes the investigation's emphasis with a rigorous review process in order to methodically address the research issues. This approach starts with the establishment of specific goals focused on ML trends and LoRaWAN network improvement. After that, there is a thorough Tool Selection phase that collects high-quality literature using main databases like Scopus, ScienceDirect, and SpringerLink. The PRISMA 2020 methodology then guides these sources through a systematic literature review process that comprises identification, screening, and a rigorous quality evaluation to guarantee that

only the most pertinent research is examined. Lastly, the framework uses technical and thematic analysis to summarize the key findings, assigning performance indicators and application sectors to particular machine learning algorithms while pointing out important research gaps and future prospects for the ML-LoRaWAN



**Figure 5:** Systematic process adopted for this review

Therefore, the following four Research Questions (RQs) are established in order to address the trends and issues outlined in this review:

1. **RQ1:** Which Machine Learning (ML) approaches are currently being used in Internet of Things (IoT) applications that include LoRaWAN technology?
2. **RQ2:** What are the performance measures used to evaluate the effectiveness of ML-LoRaWAN integration?
3. **RQ3:** Which are the main application sectors where LoRaWAN technology boosted by machine learning is most commonly used?
4. **RQ4:** In the current literature on ML-LoRa integration, what are the research gaps and recommendations for future work?

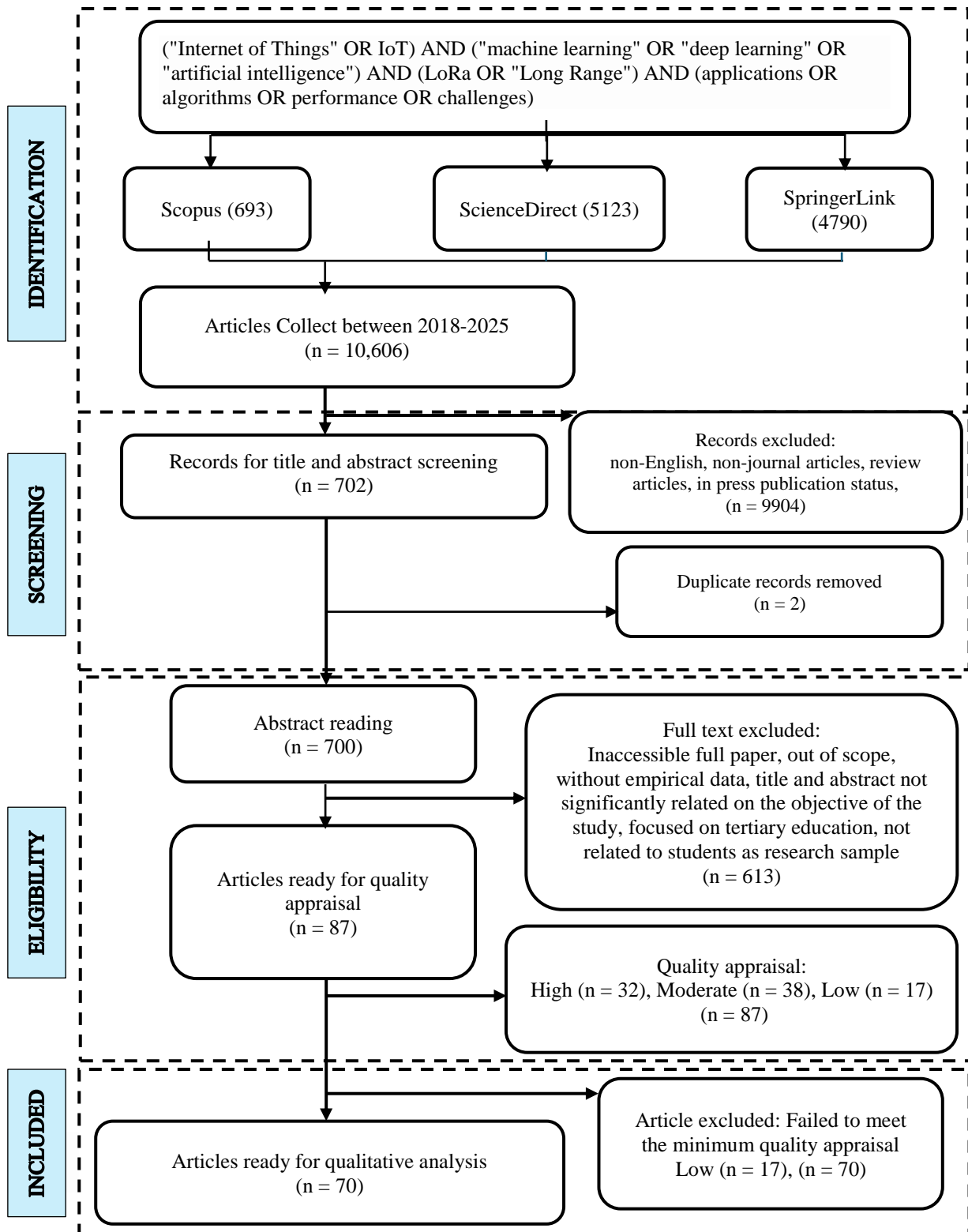
To ensure the proposed research objectives are met, this systematic literature review is structured to address specific questions that connect the current literature to the machine learning method to improve the LoRaWAN algorithm. The objective of this study is to systematically organize, examine, and investigate existing research paths for integrating LoRa technology with machine learning in Internet of Things systems, while accounting for identified research gaps. Thus, the goal of this review is:

1. To identify and categorize the various Machine Learning (ML) approaches and methods currently implemented within LoRa-based Internet of Things (IoT) applications.
2. To compare the performance measures used to measure ML-LoRa integration.
3. To study the primary application sectors where LoRaWAN technology is enhanced by ML.
4. To synthesize current research challenges and recommendations in the field of intelligent LoRaWAN networks.

#### 4.3 Systematic Searching Strategies

This study conducted a systematic literature review (SLR) to evaluate the current machine learning methods for altering and implementing algorithms in LoRaWAN networks. The review adhered to the PRISMA procedure, which comprises four main stages: identification, screening, eligibility, and inclusion, to guarantee a thorough selection of relevant publications. Only excellent research on

merging machine learning with LoRaWAN is included, thanks to this methodical strategy. Figure 6 shows the detailed workflow of the article selection and review procedure used in this study.



**Figure 6:** PRISMA Flow diagram. Based on data from Scopus, ScienceDirect and SpringerLink

### 4.3.1 Identification

The PRISMA protocol's first step is identification, which aims to methodically gather pertinent material for review. Three main databases are Scopus, ScienceDirect, and SpringerLink. This database was chosen for this investigation because of their standing as thorough archives of excellent, peer-reviewed technical research and because they are compatible with institutional access for effective data extraction. The developed research questions served as the basis for the search strategy, which combined primary keywords (Tawfik et al., 2019) and their derivatives, with a particular emphasis on "LoRa/LoRaWAN", "Machine Learning Integration" and "Application Trends". Boolean operators (AND and OR) and double quotes ("") were used to create a strong search string that was applied to titles, abstracts, and keywords in order to guarantee accuracy. 10,606 records were found for additional screening after this methodical search was limited to the publication window of 2018 to 2025. Table 1 displays the search terms used in this investigation for each of the three databases. The string terms for Scopus is different from ScienceDirect and SpringerLink.

**Table 1:** Search string used for article searching

Database	String
Scopus	("Internet of Things" OR IoT) AND ("machine learning" OR "deep learning" OR "artificial intelligence") AND (LoRa OR "Long Range") AND (applications OR algorithms OR performance OR challenges)
ScienceDirect	(IoT OR "Internet of Things") AND (ML OR "Machine Learning" OR AI) AND (LoRa OR "Long Range")
SpringerLink	

### 4.3.2 Screening

A crucial part of the PRISMA structure is the screening step, which uses particular inclusion and exclusion criteria to reduce the initial search results to the most pertinent literature. A primary review of the titles and abstracts of the first 10,606 articles found led to the removal of 9,904 records that did not fit the study's criteria. Non-English publications, non-journal articles, review articles, papers published before 2018, and papers with an "in-press" status were all excluded. All search results were saved as RIS files and imported into Mendeley Desktop in order to handle the remaining records. Only two duplicate entries were methodically found and eliminated, leaving 700 distinct articles for the following step. This process is showed at Table 2 below that include inclusion and exclusion criteria.

**Table 2:** Inclusion and exclusion criteria

Criteria	Inclusion Criteria	Exclusion Criteria
Language	English	Non-English
Timeline	Published between 2018 – 2025	Published before 2018
Publication Type	Research articles	Non-journal articles (e.g., books, conference, theses)
Article Type	Primary research articles	Review articles
Publication Stage	Final published version	In-press publication status
Study Focus	Machine learning and LoRa technology	Out of scope, inaccessible full paper, or studies without empirical data

### 4.3.3 Eligibility Criteria

The quality and applicability of the chosen research were guaranteed by the establishment of precise eligibility requirements. Only recently published scholarly works discussing the integration of ML methods with LoRa-based Internet of Things (IoT) systems were eligible for inclusion. Only conference papers and peer-reviewed journal publications published between January 2020 and May 2025 were taken into consideration because this time frame represents the most recent developments in ML–LoRa applications. 700 distinct articles made it to the eligibility evaluation stage after the screening process. This step makes sure that the chosen studies' content directly relates to the goals and research questions. In order to confirm the appropriateness of each article, a manual assessment of the titles and abstracts was carried out.

Based on a number of factors, including inaccessible full papers, studies that were outside the scope of the evaluation, a lack of empirical data, or titles and abstracts that had no bearing on the study's goals, 613 publications were eliminated from this review. Articles that did not use students as the primary research sample or that concentrated on post-secondary education were also eliminated. As a result, 87 papers were judged qualified and prepared for quality evaluation.

### 4.3.4 Quality Appraisal

The remaining 87 articles were sent to two independent experts in the field for quality assessment in order to guarantee that the content of the chosen articles in the eligibility process is of high quality as recommended by (Tawfik et al., 2019). An assessment form was used for the quality appraisal procedure, and the experts categorized each article according to three quality ranks: low, moderate, or high. Only publications classified as moderate or high quality were taken into consideration for final evaluation, in accordance with the specified protocol. 38 articles were evaluated as intermediate quality and 32 articles were regarded as excellent quality by the experts. Based on the predetermined criteria, 17 articles were rated as low quality once the quality evaluation was completed. These articles were therefore not included in the study. As a result, 70 articles in all were judged qualified and added to the qualitative analysis and the year is between 2020 – 2025 only. As a result of this evaluation, only studies of high or moderate methodological quality were synthesized, and the results are now provided in Table 4 below. Table 3 shows that (36.8%) were categorized as good quality, guaranteeing a strong basis for the systematic review. In order to preserve the technical depth and integrity of the performance study for the integration of LoRa and machine learning, studies classified as low quality (19.5%) were not included in the final synthesis.

**Table 3:** Quality Appraisal Assessment Form Result

Quality Category	Number of Papers	Percentage (%)	Justification
High Quality	32	36.8%	Articles that optimize LoRaWAN network parameters (such as SF, ADR, Security, Collision Mitigation, and Energy) directly using ML/DL.
Moderate Quality	38	43.7%	ML is applied to the application data rather than the network itself in articles that employ LoRaWAN for data transfer.
Low Quality	17	19.5%	Articles that concentrate on other technologies (such as WiFi or 5G) or that only describe IoT/LoRa without clearly implementing machine learning

## 5. RESULT AND FINDINGS

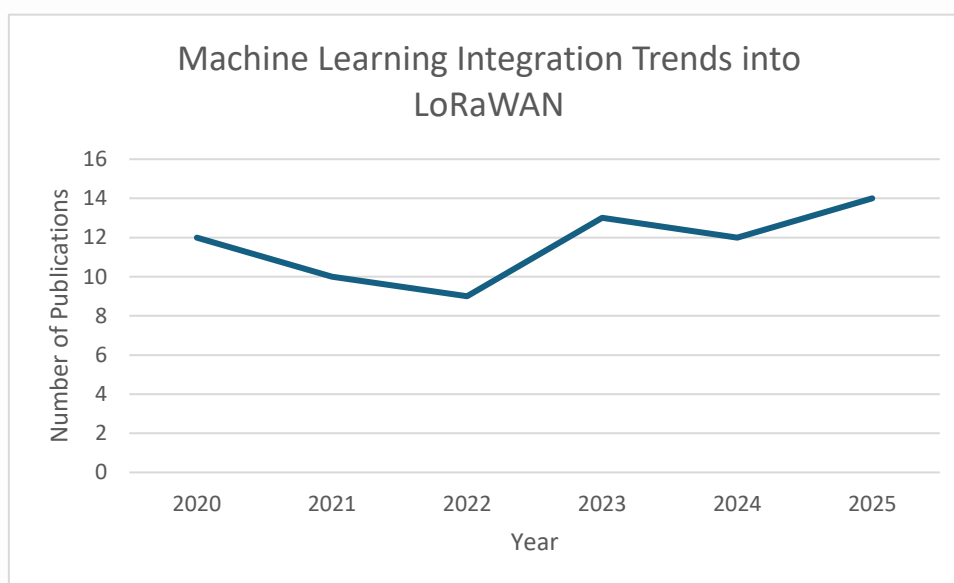
A final number of 70 articles that satisfied the inclusion and quality requirements for qualitative synthesis were found through the systematic literature review. The present level of research on the integration of machine learning algorithms trends in LoRa/LoRaWAN network designs is represented by these publications.

### 5.1 Overall Trends

After included process, only 70 articles remain and the period is from 2020 to 2025 which is in six years show the trends of machine learning integration with LoRaWAN technology. Figure 7 shows the distribution of research articles that concentrate on integrating ML techniques to improve LoRaWAN performance. The data shows a strong and continuously high level of scholarly interest in this field.

First, from 2020 to 2022, the output remained consistent, averaging about 10 publications annually. The foundational investigation of machine learning techniques like Random Forest, SVM, and K-Means in stabilizing LoRaWAN connectivity and localization is reflected in this phase. Nonetheless, there is a noticeable rising trend that begins in 2023 and peaks in 2025 with 14 publications. In order to handle new issues in LoRaWAN, such as network congestion, adaptive data rate (ADR) optimization, and energy depletion in dense IoT installations, increasing attention is being paid to more sophisticated neural networks, such as LSTM and Reinforcement Learning.

The consistent expansion throughout this period highlights the transition of the scientific community from theoretical modeling to intelligent, useful optimization. It appears that the need for autonomous, machine learning-driven performance tweaking will become a top research goal as LoRaWAN extends into more vital and dynamic applications, such smart agriculture, healthcare, and industrial monitoring.



**Figure 7:** ML integration Trends into LoRaWAN

To guarantee a clear and structured presentation of the findings, the study's results are arranged in accordance with the two research questions. Following the PRISMA selection and eligibility process, 70 papers from the original screening of 10,606 studies were kept for full text analysis. The most pertinent and reliable data on the combination of LoRa technology and machine learning (ML) in Internet of Things (IoT) applications can be found in these final studies.

The results based on the study objectives are shown in the ensuing subsections, with particular attention to the kinds of machine learning techniques used, the LoRa network designs employed, and the performance metrics given across different IoT application areas. Table 1 summarizes the 70 selected studies, outlining each study's methodology, country of origin, application domain, ML

approach, and the key performance indicators evaluated. These studies form the foundation for the subsequent discussion and conclusions.

**Table 4:** The articles that have been considered for this study are from Scopus, ScienceDirect, and SpringerLink databases

No	Author	Country	ML Technique used	Performance Metric	Application	Gap/ Future Recommendations
1	(Taneja et al., 2020)	Ireland	Clustering (K-means)	Network Bandwidth Consumption, accuracy, latency, energy	Smart Dairy Farming	Advanced Deep Learning
2	(Francesca et al., 2020)	Italy	k-means, LSTM, Decision Trees (DT)	Inter-arrival Time (IT), ERROR RATE (ER), RSSI, SNR, SF	IoT Environments	Optimize channel and network
3	(Anjum et al., 2020)	Pakistan	Decision Trees (DT), SVM	Localization Accuracy, RSSI, MSE	Smart City	Hybrid Systems
4	(S. Kim & Kim, 2020)	South Korea	Deep Neural Network (DNN)	Transmission Delay, PDR	LoRaWAN Optimization	Real-time Learning
5	(Anh Khoa et al., 2020)	Vietnam	Decision Tree & Random Forest, ANN, SVM	Accuracy, Precision, & Recall, RSSI	Smart Campus	Dynamic Route Optimization
6	(Cui & Joe, 2020)	South Korea	Long Short-Term Memory (LSTM), deep Learning (DL)	Collision Prediction Accuracy, MSE, network throughput	Industrial IoT	Real world Deployment
7	(Moy et al., 2020)	France	Multi-Armed Bandit (MAB)	Collision Mitigation, Packet Success Rate (PSR), energy autonomy	Ultra-dense IoT Networks	Multi-parameter Learning
8	(Han et al., 2020)	China	Random Forest (RF), (k-NN) & (SVM)	Accuracy, packet loss rate, latency	Smart City	Energy saving optimization
9	(Park et al., 2020)	South Korea	Q-Learning, Deep Q-Network (DQN)	Transmission Power (TP), SF, PDR, Energy Consumption, Throughput	LoRaWAN technology	Study Mobility Device
10	(Ali et al., 2021)	Indonesia	Deep Learning	Mean Localization Error (Ralat Lokasi)	Smart Building	Tested in a large-scale and a lot of

			(DNN - Deep Neural Networks)	Purata), RSSI, robustness		radio interference.
11	(Sallang et al., 2021)	Malaysia	Deep Learning, CNN	Classification Accuracy, latency, RSSI, SNR	IoT & LoRa-GPS Integration	Advanced Object Detection
12	(Mashhad i et al., 2021)	France	Random Forest (RF)	Localization Accuracy, detection Accuracy, sensitivity Accuracy	Smart Water Systems	Real-time Implementation
13	(Minea et al., 2021)	Romania	Artificial Neural Networks (ANN)	Response Time, jitter, latency	Telecommunications	Automated Root Cause Analysis
14	(Bravo-Arrabal et al., 2021)	Spain	Multi-access Edge Computing (MEC)	Signal Coverage, packet loss, latency, autonomy	Emergency Robotics	Swarm robotics
15	(Lázaro et al., 2021)	Spain	K-Nearest Neighbors (KNN), svm, RF	Classification Accuracy, RSSI, Bit Error Rate (BER), Sensitivity	Indoor localization	Combine data location and sensors
16	(Hamdi et al., 2021)	Qatar	Deep Reinforcement Learning (DRL), PPO	Energy Efficiency, Qos	Green LoRa Networks	Multi-Gateway Cooperation
17	(Singh et al., 2022)	India	Artificial Neural Networks (ANN), SVM, KNN	Soil Moisture, Temperature & Humidity, Packet Loss & Throughput, Energy consumption, Prediction Accuracy	Smart Cities	Big data analytics
18	(Wang et al., 2022)	China	Fuzzy Support Vector Machine (FSVM)	Packet Collision Rate, PDR, throughput, energy efficiency, RSSI, SNR	LoRaWAN Gateway	Dynamic network loads
19	(Sheng et al., 2022)	Taiwan	Random Forest (RF)	Classification Accuracy, Processing Time	Smart Farming	Deep Learning (CNN)
20	(Hamdaoui & Elmaghoub, 2022)	United States	Convolutional Neural Networks (CNN).	Classification Accuracy, Robustness	(IoT Security)	Adaptive Learning
21	(Zaidi et al., 2022)	United Kingdom	TinyML (Tiny Machine Learning)	Memory Footprint, energy, latency	Smart Agriculture	Automated ML (AutoML) for TinyML
22	(Abdelghany et al., 2022)	France	Multi-Armed Bandit (MAB),	ESP (Effective Signal Power),	Smart City, pemantauan kesehatan,	Algorithm configuration for each

*continued*

			Quality of Channel Allocation (QoC-A)	RSSI, SNR, PDR, Convergence time	ternakan, dan pengawasan	unique IoT characteristic
23	(Morato et al., 2023)	Italy	Artificial Neural Networks (ANN)	Spreading Factor (SF) & Payload Size	Industrial IoT (IIoT)	Developing an algorithm for dynamic transmission parameter adjustment
24	(Gandhi, 2023)	India	K-Nearest Neighbor (KNN)	Accuracy, Latency	Poultry Farming	Computer Vision
25	(Atan et al., 2023)	Turki & Jerman	Deep Neural Networks (DNN)	Execution Latency, energy	Edge Computing Networks	Reinforcement Learning (RL)
26	(Aqeel et al., 2023)	United Kingdom	Support Vector Regression (SVR)	Mean Absolute Error (MAE)	Node Localisation	Dynamic Environments
27	(Bertocco et al., 2023)	Italy	XGBoost, RF	Root Mean Square Error (RMSE), RSSI	Internet of Underground Things (IoUT)	Integration temperature impact
28	(Sabovic et al., 2023)	Belgium	TinyML (Tiny Machine Learning), CNN	Energy Consumption, Accuracy, Inference Time, Throughput & Latency	IoT without battery	On-Device Learning
29	(Farhad, 2023)	South Korea	Reinforcement Learning (RL) & Deep RL, SVM, Random Forest (RF), CNN, and RNN/LSTM, k-means	Collision Rate, PDR, throughput, latency, RSSI & SNR, energy efficiency	Smart Cities	Open Dataset
30	(Dakdouk et al., 2023)	France	Multi-Armed Bandits (MAB)	Collision Rate, PSR	LoRaWAN Network	Heterogeneous Networks
31	(Zhao et al., 2023)	United Kingdom	Multi-Agent Reinforcement Learning (MARL), Deep Q-Network (DQN)	Energy Efficiency, PDR, SF, TP, Path loss	Smart Infrastructure	Heterogeneous Soil Conditions
32	(Teymuri et al., 2023)	Iran	Multi-Armed Bandit (MAB)	Energy Consumption, PDR, Reliability, TP, SF	LoRaWAN (Low Power Wide Area Network) and Mobile IoT	Mobility Device

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33	(Artetxe et al., 2024)	Spain	Fuzzy Logic	(Soil Moisture), RSSI, SNR	Smart Irrigation	Weather Forecast Integration
34	(Ramadan et al., 2024)	Malaysia	YOLO (You Only Look Once), CNN	LoRaWAN Coverage & RSSI, Response time, Detection accuracy	AI-powered Drones (UAV)	Adaptive Path Planning
35	(Mahbub et al., 2024)	United Arab Emirates (UAE)	CNN	Inference Time, Accuracy, SNR	Biodiversity Monitoring	Cloud Integration
36	(Lavanya et al., 2024)	India	Random Forest Regression	Mean Absolute Error (MAE) & Mean Squared Error (MSE)	Internet of Medical Things (IoMT)	Deep Learning (RNN/LSTM)
37	(Kyi & Taparugsanagorn, 2024)	Thailand	Long Short-Term Memory (LSTM)	Root Mean Square Error (RMSE) & Mean Absolute Error (MAE)	Smart Energy Management	Edge Intelligence
38	(Yahya et al., 2024)	Malaysia	Artificial Neural Networks (ANN)	Return Loss, bandwidth, radiation pattern, gain, efficiency	LoRa Localization, Wearable IoT Devices	Advanced ML Models
39	(Al-hourani, 2024)	Australia	Convolutional Neural Networks (CNN)	Authentication Accuracy, SNR	(Physical Layer Security)	Integration with Existing Protocols
40	(Fahaad Alumfareh et al., 2024)	Saudi Arabia	Isolation Forest (iForest), K-Means Clustering	Data Transmission Latency, battery life	Smart Farming	Hybrid ML Models
41	(Eduard et al., 2024)	Kazakhstan	Quantile Regression (QR)	Response Time, PDR, Communication Range	Railway Safety	Large Scale Testing
42	(Jimaa et al., 2024)	United Arab Emirates (UAE)	Deep Learning (DL)	Collision Probability, Throughput, PDR, energy consumption	Smart City & Industrial IoT	Reinforcement Learning (RL) Integration
43	(Hosseinzadeh et al., 2024)	United Kingdom	Random Forest (RF), (XGBoost), (KNN) & (SVR)	Signal-to-Noise Ratio (SNR) & RSSI, link budget and path loss	Reliable IoT Deployment	Dynamic Path Loss Modeling
44	(Shen & Zhang, 2024)	United Kingdom	Deep Learning (DL)	Classification Accuracy (Ketepatan Pengelasan)	Radio Frequency Fingerprint Identification (RFFI)	Domain Adaptation

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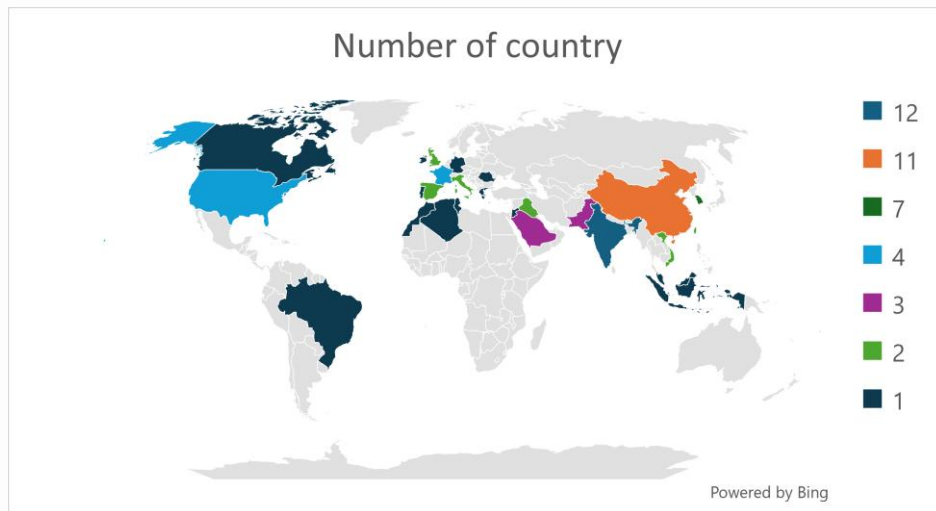
45	(Almalki & Angelides , 2024)	Saudi Arabia	Deep Reinforcement Learning (DRL)	Energy Efficiency, Data Rate & Link Reliability	Regenerative Farming	Advanced Swarm Intelligence
46	(Narsimhulu et al., 2024)	India, Turkey, and Jordan	Federated Learning (FL), Deep Learning (DL)	Model Accuracy, network latency, PDR	Internet of Vehicles (IoV), Green IoT	Integration with 6G
47	(Waly et al., 2024)	Saudi Arabia	Artificial Neural Networks (ANN)	Specific Absorption Rate (SAR), bandwidth	Medical IoT	Multi-band Support
48	(Y. Kim et al., 2024)	South Korea	RADR (Robust Adaptive Data Rate)	Data Rate (DR), PDR, Energy consumption, RSSI, SNR, Throughput	LoRaWAN in a Dynamic Environment	Integration with GPS
49	(Alwaisi et al., 2024)	Italy & Finland	Tiny Machine Learning (TinyML), KNN, RF	Energy Consumption, detection latency	Industry 4.0 & Digital Healthcare	Federated Learning
50	(Costa et al., 2024)	Netherlands & Brazil	Dijkstra's Algorithm	Energy Consumption Efficiency, network coverage, RSSI	Smart City	Dynamic Resource Allocation
51	(Khan et al., 2024)	China	Distributed Machine Learning (DML), K-means Clustering	Interference Mitigation, PDR, Energy, throughput	Intelligent Transportation System (ITS), green energy	Dynamic Traffic Management
52	(Liao et al., 2024)	Taiwan	Environmental Sound Classification (ESC)	Classification Accuracy, real-time, scalability	Forest Surveillance	Attention-based CNN
53	(Chourlias et al., 2025)	Greece	(RF), XGBOOST, Shapley Additive Explanations (SHAP), LSTM	Mean Absolute Error (MAE)	Smart Farming	Mobility Sensor
54	(Saxena, Agarwal, Nagrath, Jayavanth , Thulasidos, Maheswari, & Sasikumar, 2025)	India	YOLOv8 (You Only Look Once v8)	mAP (mean Average Precision), energy consumption, Inference Speed, classification accuracy	Smart Tomato Farming	Integrate AI predictive results automatically

55	(Bonfanti et al., 2025)	Italy	K-Nearest Neighbors (KNN), RF, SVM, Decision Trees (DT)	Accuracy, sensitivity	Livestock Monitoring	Real-time Processing algorithm
56	(Owusu et al., 2025)	Ghana	Convolutional Neural Networks (CNN)	Classification Accuracy, energy consumption, Inference Latency	Physical Layer Security	Real Hardware Implementation
57	(Kaur et al., 2025)	United States	Long Short-Term Memory (LSTM), Deep Learning (DL)	Accuracy	Security of IoT Devices	Integrating Explainable AI (XAI)
58	(Islam et al., 2025)	Australia	Siamese Network (Rangkaian Siamese)	Peak Signal-to-Noise Ratio (PSNR)	IoT agriculture	Dynamic algorithm backgrounds
59	(Lutfie et al., 2025)	Indonesia	Hierarchical Clustering (Agglomerative)	Coverage Probability, number of gateways, distance	Smart City & Industrial IoT	Integration with Spreading Factor (SF)
60	(Sharma et al., 2025)	India	Self-Attention Deep Neural Network (SA-DNN), Explainable AI (XAI)	Interpretability, robustness, accuracy	Intrusion Detection System (IDS) for IoT	Real-time dynamic Deployment
61	(Kasprzyk & Rychlicki, 2025)	Poland	Random Forest (RF), SVM, KNN, Decision Trees (DT) & Naive Bayes (NB), xgboost	Computational Efficiency, detection accuracy	Long-Range Sensor Networks (LoRa)	Develop Adaptive Learning Model
62	(Frontera-Bergas et al., 2025)	Spain	Platform IoT Multi-Sensor	Energy Efficiency, light exposure	Smart Healthcare	AI-based data analysis
63	(Onsu et al., 2025)	Canada	Long Short-Term Memory (LSTM) & Gated Recurrent Unit (GRU)	Data Labeling Efficiency, accuracy, latency	Autonomous Driving	Develop Real-time Adaptive Learning model
64	(Maulud & Aminifar, 2025)	Iraq	Artificial Neural Networks	Localization Accuracy, Scalability	Smart Warehouse & Workplace	Develop Dynamic Environment

*continued*

			(ANN), KNN, RF			t Adaptation model
65	(Alhattab et al., 2025)	Saudi Arabia	Reinforcement Learning (RL), Q-learning	Network Scalability, PDR, energy, throughput	Long-Range Networks	Integration with Edge Computing
66	(Mutescu et al., 2025)	Romania	Convolutional Neural Networks (CNN)	Classification Accuracy, SNR, inference time	Smart Cities & Agriculture	Develop Real-time Dynamic Access protocol
67	(Munaguri et al., 2025)	India	Long Short-Term Memory (LSTM)	Prediction Accuracy (RMSE/MAE), Network Latency & Throughput	Smart Agriculture	Processing LSTM data at the gateway level
68	(Suprava et al., 2025)	India dan Jordan	Recycle CNN, Deep Learning (DL)	Classification Accuracy, Real-time Monitoring	Smart Waste Management	Develop Solar-Powered Smart Bins
69	(Xu et al., 2025)	China	Regression Analysis	RSSI (Received Signal Strength Indicator), SNR (Signal-to-Noise Ratio), Packet Loss Rate, dan Path Loss.	Agricultural IoT	Integrate ML techniques to build models that are more dynamic and adaptive.
70	(Pan, 2025)	Taiwan	Artificial Intelligence of Things (AIoT)	Accuracy, Sensitivity, & Specificity, SNR	Healthcare	Use Cloud-based Deep Learning

India (12 publications) and China (11 publications) are the two countries with the largest research focus in Asia, according to the geographic distribution of the 70 examined papers showing at Figure 8 below. The main drivers of this regional domination are the extensive national shifts towards precision agriculture and Smart City infrastructures, where LoRaWAN's low-power and long-range capabilities provide an affordable substitute for conventional cellular networks. Machine learning is essential in these broad, heavily populated agricultural areas to minimize signal collisions and maximize network capacity. Additionally, a specialist focus on industrial automation and energy autonomy is reflected in the prominent representation of South Korea (7 publications) and several European countries, including France and Italy. These results imply that regional needs influence the research landscape, with Europe and North America giving priority to industrial standardization and sustainability regulations, while Asia concentrates on scalability for large-scale deployments.



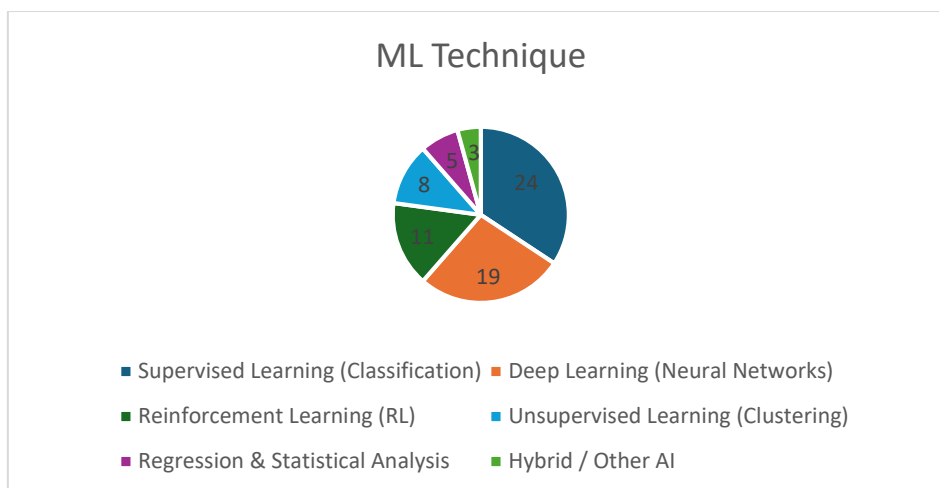
**Figure 8:** Number of articles published according to country

## 5.2 Result for Research Question

This section summarizes the results of a thorough examination of 70 carefully chosen, peer-reviewed publications that met the predetermined study questions. Key trends, approaches, and performance indicators pertinent to the integration of machine learning in LoRaWAN are identified by the review through the synthesis of data from these many researches. A data-driven response to the main goals of this systematic literature review is provided by the results, which are categorized to give a thorough picture of how different machine learning methods improve network efficiency, scalability, and energy longevity.

### 5.2.1 RQ1: Categories of ML Techniques in LoRaWAN

Regarding to Figure 9 below, the examination of the 70 chosen studies shows a wide variety of machine learning techniques applied to improve LoRaWAN performance. About 34% of the research use supervised learning, which is still the most used method. Support Vector Machines (SVM) and Random Forest (RF) are two common algorithms used for signal classification and localization tasks. Deep learning, which uses architectures like Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) for sophisticated time-series prediction and collision mitigation, comes in second (27%). Remarkably, Reinforcement Learning (16%) is on the rise, indicating a move toward self-adaptive and autonomous network control. The other research use regression analysis for path-loss modeling and unsupervised clustering for node organization. According to this distribution, the academic community is quickly shifting towards more complex, data-intensive neural networks to handle dynamic IoT situations, even while traditional ML models are still fundamental.



**Figure 9:** ML Techniques in LoRaWAN

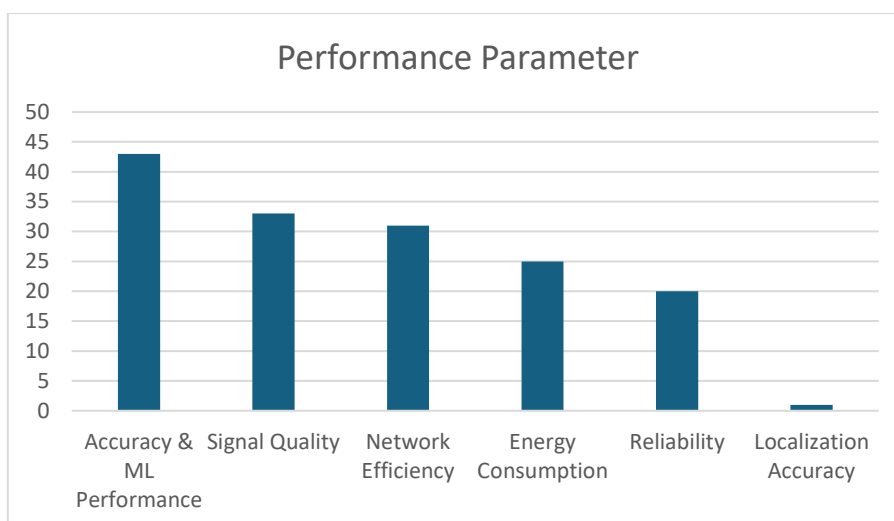
As illustrated at Table 5 below, the following table outlines the taxonomy of Machine Learning methods identified in this review, including supervised, unsupervised, and reinforcement learning, along with specific examples utilized in the literature.

**Table 5:** Taxonomy of Machine Learning Methods in LoRaWAN

Learning Category	Algorithm Examples	Primary Application in LoRaWAN
Supervised Learning	KNN, Random Forest, SVM, CNN, LSTM	Soil moisture prediction, healthcare monitoring, and biodiversity tracking.
Unsupervised Learning	K-Means, PCA	Pattern recognition and data dimensionality reduction in sensor networks.
Reinforcement Learning	Q-Learning, DQN	Dynamic slot allocation and autonomous network scalability.

### 5.2.2 RQ2: Performance Parameters for ML-LoRa Integration

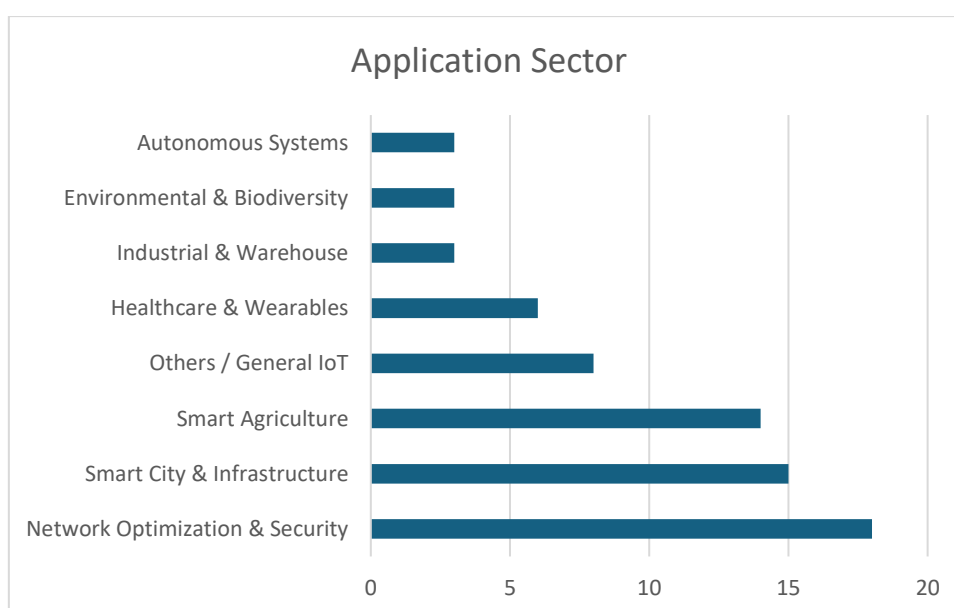
A number of critical performance measures that are used to assess the efficacy of machine learning models in LoRaWAN contexts were discovered by the systematic study based on Figure 10. Classification accuracy, precision, and error rates (MSE/RMSE) are among the most commonly used metrics under 'Accuracy and ML Performance' (43 articles), which reflects the main emphasis on the dependability of the ML models themselves. 'Network Efficiency' characteristics like latency and throughput (31 articles) and 'Signal Quality' measures like RSSI and SNR (33 articles) come next. In 25 studies, "Energy Consumption" is still a crucial parameter, highlighting LoRaWAN's fundamental need for low-power operation. Additionally, 20 publications used "Reliability" metrics to gauge the success of end-to-end communication, particularly Packet Delivery Ratio (PDR) and packet loss. The variety of these indicators suggests that ML-LoRa integration is assessed based on its observable effects on network resilience and energy longevity in addition to its computational accuracy.



**Figure 10:** Performance parameter in ML-LoRa integration

### 5.2.3 RQ3: Major Application Sectors for ML-LoRaWAN

The analysis research from 2019 until 2025 shows that the systematic research finds that LoRaWAN technology, augmented by machine learning, is most frequently used in a wide range of application industries at Figure 11. 'Network Optimization and Security' (18 publications) makes up the largest section, demonstrating the importance of the research community in addressing basic protocol issues such as signal interference and scalability. 'Smart City and Infrastructure' (15 articles) and 'Smart Agriculture' (14 articles) are the key industrial fields that take advantage of LoRaWAN's long-range capabilities to facilitate extensive urban and rural monitoring. 'Healthcare and Wearables' (6 articles) and 'Industrial IoT' (3 articles) also show a great deal of research interest, as these fields use machine learning algorithms to detect anomalies in real time and improve operational efficiency. The emergence of new industries like "Autonomous Systems" (drones/robotics) and "Environmental Monitoring" indicates that ML-LoRa integration is becoming more flexible and can meet the various requirements of both fixed and mobile IoT settings.



**Figure 11:** Application sector in ML-LoRaWAN integration

#### 5.2.4 RQ4: Research Gaps and Future Recommendations for ML-LoRaWAN

While general protocol optimization is still a common issue, there is a notable research trend (27.1%) toward real-time and dynamic adaptation, according to the synthesis of the 70 examined publications, as shown in Figure 12. This implies that autonomous, context-aware systems that can react instantly to changes in their surroundings will replace static setups in future LoRaWAN deployments.

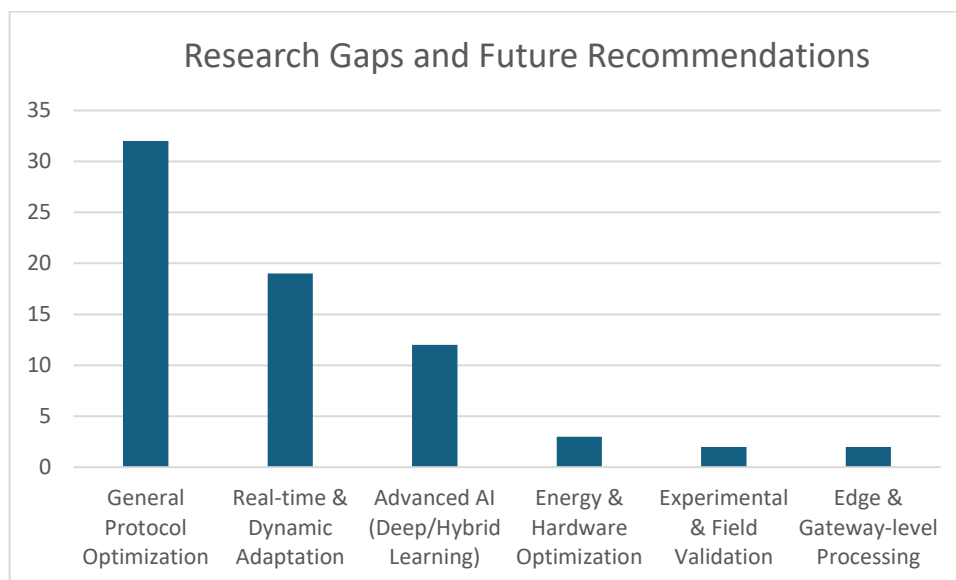


Figure 12: Research Gap and future recommendations in ML-LoRaWAN integration

## 6. Discussion and Gap Analysis

From simple heuristic models to complex deep learning architectures, the chosen examples demonstrate a notable evolution in the integration of ML inside the LoRaWAN ecosystem. The most popular method for classifying and localizing signals is still supervised learning, however in order to manage the complexity of extremely dense IoT environments, there is a noticeable trend toward reinforcement learning and deep learning. According to the statistics, performance measures are now more focused on overall network health, including packet delivery ratios, energy lifespan, and latency, rather than just basic signal strength (RSSI/SNR). This shift demonstrates how the academic community has realized that static network topologies are inadequate for the dynamic and uncertain nature of contemporary IoT deployments, like large-scale precision agriculture and smart cities.

Even with these developments, a number of important research gaps still need to be filled. The majority of the literature currently in publication is on short-term field experiments or laboratory-simulated environments, leaving a dearth of longitudinal data on the performance of ML models under various environmental variables, such as shifting urban topographies or seasonal crop growth. Studies that concentrate on "Edge AI," which offloads ML processing to the gateway level in order to decrease latency and cloud dependency, also clearly lack this feature. Future studies should focus on creating lightweight, self-adaptive algorithms that can be used on hardware with limited resources. This will guarantee that intelligent LoRaWAN parameter optimization is both energy-sustainable and real-time for extended field operations.

The summary table 6 below highlights a major shift in the field of LoRaWAN research and summarizes the main conclusions of this thorough literature assessment. The information shows that although most performance gains are still supported by standard supervised learning, deep learning and autonomous adaptation are becoming more and more popular in order to satisfy the needs of precision agriculture and smart cities. Additionally, the research gaps that have been

identified specifically, the requirement for edge-level intelligence and real-time dynamic modeling clearly justify the creation of more complex, context-aware algorithms. All of these findings together offer a fundamental framework for comprehending how machine learning might be strategically used to get over the present scalability, reliability, and energy efficiency constraints of LoRaWAN.

**Table 6:** Summary table for ML-LoRa integration

Research Question (RQ)	Key Findings & Trends	Most Frequent Categories
<b>RQ1: ML Approaches</b>	High dependence on categorization models, with neural networks showing a growing trend for time-series data.	Supervised Learning (34%), Deep Learning (27%)
<b>RQ2: Performance Metrics</b>	The focus of evaluation changed from pure machine learning accuracy to useful energy and network reliability indicators.	Accuracy (43), Signal Quality (33), Network Efficiency (31)
<b>RQ3: Application Sectors</b>	Strongest usage in industries that need high node density and wide-area coverage.	Network Optimization (18), Smart City (15), Smart Agriculture (14)
<b>RQ4: Gaps &amp; Future Work</b>	Autonomous adaptability and intelligence transfer from the cloud to the network edge are required.	Real-time Adaptation, Edge Computing, Field Validation

## 7. Conclusion and Recommendations

In summary, this comprehensive assessment of the literature demonstrates that LoRaWAN's use of machine learning is an essential advancement for resolving the performance issues of contemporary IoT networks, especially with regard to scalability and energy economies. The analysis of 70 core studies demonstrates a clear technological shift from basic supervised algorithms toward autonomous, deep learning-based frameworks that can better navigate the complexities of dynamic environments like smart cities and precision agriculture. However, future research must focus on creating "Edge-AI" solutions and self-adaptive algorithms that can operate in real-time on hardware with limited resources if intelligent LoRaWAN is to reach its full potential. To guarantee that ML-driven improvements are not only theoretically sound but also practically robust across different global topographies and industrial use cases, it is advised that future research concentrate on long-term field validation and the development of standardized, heterogeneous datasets.

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## CONFLICT OF INTEREST

The authors declare no conflicts of interest.

## AUTHORS CONTRIBUTION

**H.S.M. Soid:** Conceptualization, Methodology, Data curation, Investigation, Formal analysis, Writing – Original draft preparation. **M.H.A. Majid:** Supervision, Validation, Project administration, Formal analysis, Visualization, Writing – Review and Editing. **A.B. Ibrahim:** Methodology, Resources, Validation, Writing – Review and Editing. Formal analysis, Visualization, Writing – Review and Editing.

## AVAILABILITY OF DATA AND MATERIALS

Please choose one of the applicable statements below.

1. Data available within the article or its supplementary materials.

## DECLARATION OF GENERATIVE AI

During the preparation of this work, the author(s) used Gemini Google to enhance the clarity of the writing. After using the Gemini Google, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

## ETHIC STATEMENTS

Not applicable

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