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A Systematic Review of LPWAN and Short-Range Network using AI to Enhance Internet of Things

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Abstract—**Artificial intelligence (AI) has recently been used frequently, especially concerning the Internet of Things (IoT). However, IoT devices cannot work alone, assisted by Low Power Wide Area Network (LPWAN) for long-distance communication and Short-Range Network for a short distance. However, few reviews about AI can help LPWAN and Short-Range Network. Therefore, the author took the opportunity to do this review. This study aims to review LPWAN and Short-Range Networks AI papers in systematically enhancing IoT performance. Reviews are also used to systematically maximize LPWAN systems and Short-Range networks to enhance IoT quality and discuss results that can be applied to a specific scope. The author utilizes selected reporting items for systematic review and meta-analysis (PRISMA). The authors conducted a systematic review of all study results in support of the authors' objectives. Also, the authors identify development and related study opportunities. The author found 79 suitable papers in this systematic review, so a discussion of the presented papers was carried out. Several technologies are widely used, such as LPWAN in general, with several papers originating from China. Many reports from conferences last year and papers related to this matter were from 2020-2021. The study is expected to inspire experimental studies in finding relevant scientific papers and become another review.**

Keywords—Artificial Intelligence (AI); Internet of Things (IoT); Low Power Wide Area Network (LPWAN); Preferred reporting items for systematic reviews and meta-analyses (PRISMA); Short-Range Network

I. INTRODUCTION

The digital world has developed rapidly, one of which is the developing Internet of Things (IoT). This technology is thought to be part of a breakthrough that can help various groups of people, this technology is also overgrowing, and multiple kinds of research have been carried out that utilize IoT [1], [2]. Another thing because of its application in various fields and form something new proposed such as; Smart Farming[3]–[5], Smart Health [6]–[8] dan smart cities [9].

In its application, the Internet of things or IoT[10]–[13] cannot work alone. It needs other device assistance, such as that offered by the Low Power Wireless Area Network (LPWAN), which guarantees low and long-distance systems working in remote areas for an IoT communication system. IoT implementation requires a node with low complexity and energy-saving specifications when using a scalable network. Recently, wireless technologies such as IEEE 802.11, IEEE 802.15.1 Bluetooth, wireless local area network (WLAN), and IEEE 802.15.3 ZigBee can be exploited. As Bluetooth and WLAN are proposed because it can have high-speed data communication, other technologies such as ZigBee are used for systems with low data rates in on-premises environments [14].

LPWAN was formed to be one of the solutions for supported Internet objects such as Sigfox, LoRa, and LTE-M. This technology is proposed to be able to receive and send messages with small data but has a very long transmission distance, reaching up to 40km. One reason for this technology is that the equipment used does not consume much power and is very cheap [15]. LPWAN technology is very suitable for connecting equipment that needs to transmit small data over long distances while ensuring the data can be sent correctly. In IoT applications, it only has to transmit a small amount of data that provides information. Low power consumption makes it possible for this device to perform this task with the least cost and less energy consumed [16].

LPWAN technology can be divided into 2 parts: LPWAN technology that works on spectrum licenses and spectrum licenses [17] and other technology working on the licensed spectrum. There are several technologies and research such as: Narrowband IoT (NB-IoT) [18], [19], LTE-M [20], [21] or utilize cellular IoT [22] dan EC-GSM-IoT [23], [24]. Meanwhile, LPWAN technology that works on the unlicensed spectrum, such as: Long Range (LoRa) [25], Sigfox [26], [27], RPMA [28], [29], Weightless [30], etc. LPWAN technologies, such as LoRa and Sigfox, can provide a guarantee in terms of assisting IoT applications. These carry out significant development where they greatly contribute to enhancing connections in existing devices to be transmitted to the Internet. The power used is very efficient in operating IoT applications [31]. Another thing is that other LPWAN technologies are also needed, such as LTE-M, NB-IoT, etc., especially those used in IoT.

In addition to utilizing LPWAN, there are several technologies used in IoT for short-range communication or Low Power Short Range Networks, commonly called Short-Range Networks, such as; Ipv6 Low Personal Area Network (6LowPAN). This technology can realize IPv6 packet transmits on IEEE 802.15.4 based on the WSN standard. 6LoWPAN, which can be said as one of the most suitable technologies for learning a connection between the Internet and WSN, this technology is also the key to carrying out IoT development [32] and ZigBee. This technology is the into communication that has existed for a few years because it works based on the IEEE 802.15.4 standard for the wireless personal area network (WPAN) between various ad-hoc devices such as PCs, headsets, mobile phones, and Multimedia [33].

Others technologies like Bluetooth technology have been around for a long time, but this technology is one of the key components in wireless communication. Bluetooth or Bluetooth Low Energy (BLE) provides solutions such as low cost and low power in transmitting short-distance radio. More details such as BLE have become one of the main technologies in building IoT connections [34]. Low Power Short Range technology that IoT often uses, such as Radio Frequency Identification (RFID), Near Field Communication (NFC), and ZWave [35]

Artificial Intelligence or AI [36]–[39] is a critical technology, and in enhancing science, AI is probably one of the most widespread and oldest computer sciences. This technology is because AI is related to the factor of how to imitate cognitive functions in developing systems that can think and solve real-world problems [40].

In addition, this technology can also usually be applied to various fields such as; Sentiment Analysis [41]–[43], Big Data [44]–[46], Blockchain [47]–[51], and the Internet of Things (IoT) [52]–[54]

AI drop is divided into categories like Machine Learning or ML [55]–[57] ML can be exploited like a workhorse of AI, and the intensive use of ML uses methods that can be found everywhere, almost in a large number of sciences, businesses, and engineering, which are more based on actual decision making [58]. Machine learning can be shared into several types: unsupervised, supervised, semi-supervised, and reinforcing learning (RL). Which other derivatives exist Temporal-Difference Learning [59]–[61] dan Q Learning [62]–[64] along with existing studies

As previously mentioned, RL, or Reinforcement Learning [65]–[67] as previously mentioned, is a part of AI already widely used. As the name suggests, RL can offer tools and frameworks. RL also can use for robotics to perform difficultly [68] Temporal-Difference Learning (TD Learning) is one of the simple iterative algorithms that can be used to estimate the function in the value of appropriate in carrying out the policy of giving in the Markov decision process. TD is usually referred to as one of the most widely used algorithms because it is most often used in reinforcement learning. It has a proven theoretical analysis to conduct resistance, and few guarantees of statistical efficiency are available [69].

Q-learning is one of the representative strengthening lessons that until now many researchers have implemented. approach and is an off-policy strategy. However, there are information gaps regarding this robust algorithm that can be exploited. Q-Learning was initially not good enough on several factors and included: a narrow application range. But lately, there are general advances in machine learning, which made many variants of Q-learning such as Deep Q-learning, etc [70].

Deep reinforcement learning is usually referred to as one of the revolutions in AI and represents a step in the development system independently, with the very level of knowledge. These days, deep learning can do reinforcement learn to scale problems that were previously difficult to solve [71]. Other studies about Deep Reinforcement Learning [72]–[74] (DRL) have also done a lot

Next, Deep Learning (DL) [75]–[77], DL is a derivative of ML, which usually works based on deep convolution neural networks, and it has a long history [78]. The DL method is widely used today because it has achieved fantastic results, even if it is related to human workings [79]. But in reality, these methods and technologies can work not only in software but also by helping IoT, especially in LPWAN communications and short-range networks.

With the many studies available in LPWAN, in this case, we need a forum to conduct experiments on previous studies that focus on reviewing LPWAN and short-range networks. As done by [14], the review focuses on doing definitions systematically in looking at the characteristics of existing applications

According to [35], This study features a survey that presents the view of wireless technology. This technology is still utilized in most IoT devices and offers IoT communication of a common nature and is best suited by generating and ensuring connections support real-time and uninterrupted data, of course, low energy.

According to [80], The study performs analysis and existing solutions to perform low power-based network management on IoT. Another thing, because this paper also presents a comparison of current research studies on how to manage IoT-based low-power networks on different requirements and identify other things

According to [81], This study examines the benefits of several LPWAN technologies. It can show the benefits and purposes of LoRa and Sigfox, which are minimal battery utilization, low cost through NB-IoT, and efficient power usage. This matter explains the benefits of using NB-IoT in terms of quality of service (QoS) and latency. But can be embedded in LPWAN.

Few previous studies have researched systematic reviews, especially those discussing AI. Systematic AI in helping LPWAN and Short-Range Networks enhance the performance of IoT, so this is an opportunity for authors to conduct systematic reviews by utilizing published papers. The review is used to see the potential for further research by other researchers. In this systematic review, the author uses the Preferred reporting items for systematic reviews and meta-analyses (PRISMA) [82]. by utilizing the PRISMA method, the results of a systematic review, according to the author, will produce good results.

The necessity and innovation are needed in conducting reviews on this topic, so the results of this review can help researchers, industry, and related education. This research aims to find related articles focusing on AI for LPWANs in maximizing IoT for their application in agriculture, homes, cities, etc. Reviews are carried out systematically by utilizing PRISMA so that the steps are more organized and under the given method. It is hoped that the articles provided can help researchers, industry, and other academics conduct further research either experimentally or in other new reviews.

Contributions derived from this systematic review are; to maximize the LPWAN system and short-range network systematically review to enhane the quality of IoT, look for LPWAN platforms and short-range networks in IoT, and discuss results that can be applied to a certain scope.

Finally, after presenting the background of the study according to the authors in part 1, several parts will be maximized from the results of the systematic review to organize the study. Section 2 will focus on the methodology used in conducting this study's systematic review. Next step 3, the author will describe the details of the systematic search results. In Section 4, the researcher will discuss some of the methods used. Finally, the last Part 5 is the conclusion.

II. METHODOLOGY

Many excellent scientific articles continue to develop or have been published at the end of this year. Several authors need to do a detailed analysis from different points of view to see several models suitable for research. For example, many AI-focused uses of LPWAN and Short-Range Networks in IoT show breakthroughs and challenges in carrying out the latest innovations. This study aims to analyze AI in LPWAN and Short-Range Network in enhancing the quality of IoT use utilizing PRISMA, of course, by conducting a systematic review.

It is difficult to develop a method because the author only uses the existing systematic review method. The PRISMA method was formed to facilitate a systematic search, but several studies have developed its application (inspired by a previous study [83], [84]. In this review, the author applies the development of PRISMA. Then several steps were taken to assist this systematic review, in which 3 phases were used. Fig. 1 will show the Methodology Flowchart (inspired by a previous study [83], [84]).

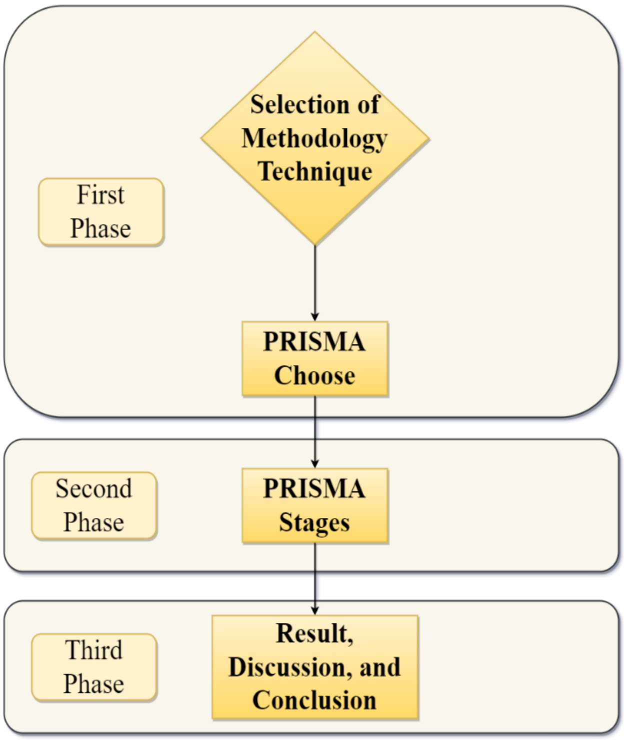

Fig. 1. Methodology Flowchart.

In Fig 1, the author has outlined the criteria, strategies, and assessments that will be used by applying PRISMA development (Inspired by a previous study [83], [84]).

According to Fig 1, several stages are described as follows:

1. Choose a suitable systematic review methodology after thinking and looking for the PRISMA reference that the author chose
2. Carry out the steps in PRISMA as a systematic review solution
3. Results from PRISMA are used in defining results, discussions, and conclusions

A. Research Strategy

In this study, the author makes a strategy. In 2022, the study conducted a highly correlated search of AI focused on LPWAN and Short-Range Networks to enhance IoT performance. The author then focuses on very relevant research.

At this time, it is done by searching for details of terms, such as ("LPWAN" OR "Low Power Wide Area Network") and ("Artificial Intelligence" OR "AI") and ("Short-Range Network" OR "Short-Range Communication") and ("Lora" OR "Long Range") and ("Sigfox") and ("NB-IoT" OR “Narrow Band-Internet of Things) and ("6LowPAN" OR “IPV6 Low Personal Area Network) and ("Bluetooth") and ("NFC OR Near Field Communication") and ("RFID" OR “Radio Frequency Identification”) and ("Cellular IoT") related to ("IoT" OR "Internet of Things) and ("Reinforcement Learning" OR "Deep Reinforcement Learning") and ("Deep Learning") and ("Machine Learning") and (“Q-Learning”) and some related research AI that can enhance the quality of IoT

After using the previously described key phrases, create an algorithm based on the search from the database. This study needs to use the main keywords that fit the existing scope. In this study, the search does not focus on only a few types of AI but its derivatives such as ML, DL, RL, DRL, and Q-Learning. In addition, the publications used only focus on using English.

B. Selection Criteria

The author searched for several papers from 2018 – 2022. The next step was also screening papers that had to talk about AI technology in LPWAN and Short-Range Networks to enhance IoT performance. But some things cannot be ignored. However, the article should still propose the benefits of AI in LPWAN and Short-Range Networks and not discuss other points. Several phases are used in selecting criteria, such as the focus on Identification, Screening, Eligibility, and Included. The most important phase that must be carried out, such as the studies used, must be in the form of research papers. Some important things such as websites and online articles that are not publications will not be utilized.

C. Quality Assessment

Information obtained from four databases resulted in 3784 papers. Next, identification is made to see several factors. In this study, identification excluded 2457 papers and left 1327 papers at screening. After that, it entered the next stage, and there were 939 exceptions, 388 papers were left in the eligibility phase, and the results were analyzed for 79 papers and excluded 309 papers. Thus, 79 papers have been the center of discussion in this study.

After doing the steps, the author will focus on classifying existing papers. So that in the next section, the results of the review selection will be explained in the next chapter.

III. RESULT

The results of the methodology in the previous explanation, but in this section, the author focuses on proposing results that will be used in proposing PRISMA [82] (and inspired by previous pattern Study [85] and [84]) concept used, as shown in Fig. 2.

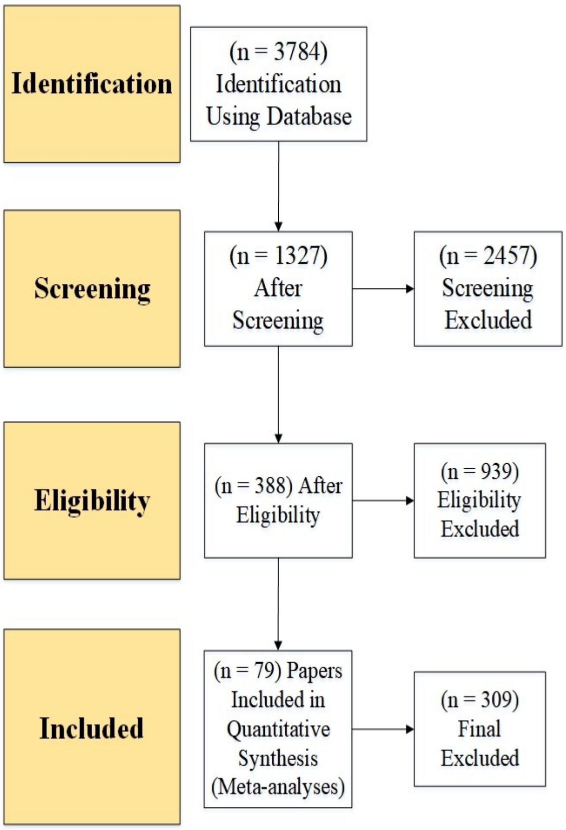

Fig. 2. PRISMA flowchart.

Fig. 2. presents several phases and results of the PRISMA search conducted by the authors in making use of this systematic review. In the picture, the author tries to find research papers from internet sources and must focus on the research objectives, namely AI studies on LPWAN and Short-Range in enhancing IoT. The author attempts to search for anything that can be useful in IoT, especially LPWAN and Short-Range communications, focusing on several related technologies, methods, and algorithms to help this review. Results Table 1 is a table that will explain from where the country of the author made the article (focus on the first author).

In Table I, this systematic review shows that many countries that study (focus on the first author) AI studies on LPWAN and Short-Range in enhancing IoT come from Asia, especially China, with 11 papers.

Next, the author will present a mapping based on the criteria of the originating paper (conference or journal). Criteria are presented in Table II.

Table II presents the results of a comparison of the number of conferences and journals. Conference Papers are utilized more than Journal papers as references in this systematic review. It shows the systematic review is mainly explained using conferences.

TABLE I. PAPERS BY COUNTRY

Country	Result
China	11
USA	7
South Korea	7
India	6
France	5
United Kingdom	5
Greece	4
Taiwan	4
Japan	3
Denmark	3
UAE	2
Norway	2
Cyprus	2
Spain	2
Canada	2
Philippines	1
Portugal	1
Morocco	1
Malaysia	1
Sweden	1
Finland	1
Russia	1
Switzerland	1
Australia	1
Montenegro	1
Colombia	1
Peru	1
Bangladesh	1
Serbia	1

TABLE II.PAPERS BASED ON CRITERIA

Database	Result
Journal	38
Conference	41

After that, the author will present the results according to the year the paper was published, which became a reference in preparing this systematic review paper, as shown in Table III.

TABLE III. PAPERS BASED ON PUBLICATION YEAR

Publication Year	Result
2018	4
2019	25
2020	17
2021	26
2022	7

Table III presents published papers by year, with the results in papers published mostly in 2019, 2020, and 2021. So, the author believes that a lot of research is presented in that year.

Based on Tables I-III, the results of a systematic review have succeeded in searching for research papers. Especially related to definitions such as; where is the researcher's country of origin, the criteria for the article, and the year of publication. Researchers or related industries can use this to see opportunities from which countryside is doing a lot of research, criteria journals, and year of publication.

In contrast to previous studies that used PRISMA but were not optimal [84], in this study, the author focuses more on the use of PRISMA than how AI on LPWAN and Short-

Range Network technology can enhance the performance of IoT.

After that, the author already knows the criteria for the research paper. The author will present a discussion in the next section. The discussion contains the author's views on AI in LPWAN and short-range networks that can enhance IoT.

IV. DISCUSSIONS

This section will discuss the results of a systematic review of AI research that helps LPWAN and Short-Range Networks enhance IoT performance. Some of the discussions will be presented in Fig. 3.

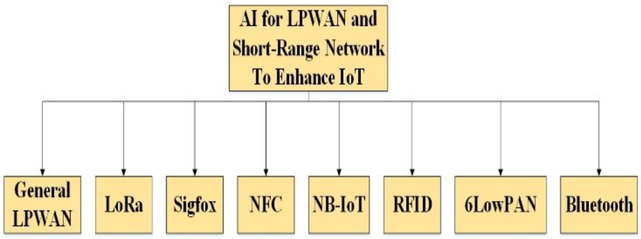

Fig. 3. Topics Discussion

In Fig 3, the author will focus on which technologies are used in LPWAN and Short-Range Networks. But the authors see a lot of research discussing LPWANs in general. The authors still use LPWAN for discussion and other parts discussed by the author, such as; LoRa, Sigfox, NB-IoT, 6LowPan, Bluetooth, NFC, RFID, and Cellular IoT.

Table IV will explain some of the results of the discussion related to the results obtained. In the next section, several studies described in Fig. 3 will be discussed in detail in several subsections.

A. *LPWAN*

In this section, the author will discuss specific research that uses LPWAN as a general term. The following are related research studies:

Orfanidis *et al.* [86] Discuss some functions in the system to LPWAN has contributed at some point in the IoT environment. Machine Learning can help embedded systems help advance the Internet of Things focused on enhancing accuracy and pattern identification. This IoT can be maximized when the components used are very good. The evaluation is carried out in several scenarios where the user can perform specific footwork.

Chen *et al.* [87] discuss current wireless communication technologies, such as technology (4G, 5G), and low power wide area technology (LPWA). These technologies such as (Sigfox, and LoRa) and other spectrums such as (LTE-M, ECGSM, NB-IoT, and LTE-M). This study puts the gradual development of IoT and AI maturity ahead of a low-power (Cognitive-LPWAN) architecture for maintaining efficient communications and stability across multiple IoTs. This study puts forward the LPWA hybrid method. To ensure AI can be used effectively, which is carried out from a traffic management perspective. The AI algorithms are used in intelligent controls for application communication, intelligent wireless technology, and other services in communication.

TABLE IV. SUMMARY OF RESULTS

Category	Result
Main findings	Many studies have focused on LPWAN compared to short-range networks. This is because LPWAN helps more efficient and inexpensive communication so that many improvisations can be done.
Comparison with other studies	There have been many systematic review studies, one of which [84] conducted research using PRISMA but only focused on one topic and did not show an increase in systematic reviews. In this review, the author tries to add a little discussion about the development of LPWAN and Short-Range Networks using AI to enhance the quality of IoT
Implication and explanation	Because LPWANs are being researched more, their development is very fast, especially remote-based ones. This LPWAN causes long-distance communication to be not difficult. With the help of existing algorithms, AI-based LPWAN as remote communication can help enhance IoT technology.
Strengths and limitations	The strength of this research, in detail PRISMA, provides a good description of the stages in conducting a systematic review. The limitation is that the review only discusses the paper's results in general and not specifically.
Recommendation and future direction	Recommendations for further research are carried out systematically, for example, components of Lora, Sigfox, etc. Not in general, LPWAN and short-range networks.

Kaburaki *et al.* [88] Discuss a basic scheme in machine learning that is simple but efficient and effective in dealing with packets experiencing collision problems by balancing the transmission time and avoiding the transmission of unneeded packets. In the Q-learning technique used in this study, each LPWAN component adjusts the delivery time, probability, and transmission time. The simulation results using a computer display when the schema has increased the average packet delivery rate (PDR).

Several studies still relevant on AI used in LPWANs and can enhance IoT performance are presented in more detail in Table V.

TABLE V. AI – LPWAN TO ENHANCE IOT

References	Topic	AI Solution
[86], [89]	Wearable Devices	Machine Learning
[87]	Intelligent Wireless	AI
[88]	Traffic Control	Q-learning
[90]	Energy Efficiency	Q-learning
[91]	Compressed Communications	Machine Learning

B. *LoRa*

This section will discuss the research using LoRa as a technology, not LPWAN. So the focus of this section is on some research focused on AI being used in LoRa to help IoT. The following are related research studies:

Li *et al*. [92] discuss that LoRa, is widely used in IoT because it is open-source and has unique, easy-to-use characteristics. This study presents NELoRa, which is used to enhance neuroprotection of the lation method, using the basic capabilities of feature abstraction found in DL in assisting ultra-low SNR LoRa. The study results show that NELoRa can be used and reaches 1.84-2.35 dB SNR.

Ikram *et al.* [93] This study utilizes a repetitive neural network (RNN) with Long Short-Term Memory (LSTM) architecture for ambient prediction temperature (AT). Studies make predictions based on Information from meteorology taken from the IoT station. This technology uses sensors to capture humidity and temperature with the LoRa protocol. The study carried out the formulation of the AT prediction problem as a time-series regression problem.

Adeogun *et al*. [94] discuss a result of the application in detecting human location and the number of people in the office who take advantage of data based on IoT-LoRa. The study performed the exposure of the problem as multi-binary and binary classification by proposing a two-layer feed-forward neural network to the data. This information utilized in validation, testing, and training consists of Information about the environment derived from IoT sensor components.

Purohit *et al.* [95] propose precisely and appropriately predicting outdoor in the location is housed indoors utilizing a deep neural network in which data is obtained utilizing the Long-Range Wide-Area Network (LoRaWAN) communication protocol contained in LoRa. The study conducted a way of interpolating the system architecture based on fingerprints. Studies proposed an autoencoder method to handle the large number of samples lost due to extensive coverage and LoRa size.

Tesfay *et al.* [96] propose a detection signal in the uplink on a LoRa-based network utilizing DL. Studies perform strategies such as regression in deep feed-forward neural network-based bit detection and classification for convolution-based symbol detection neural network. The result shows the proposed and relevant approach to dealing with scalability issues.

Sallang *et al.* [97] Discussed the research objectives to propose developing smart waste management utilizing DL models. The study focuses on enhancing the monitoring process of trash bins and waste segregation in the IoT environment. This study aims to develop smart waste management by utilizing a DL model to enhance the way to sort waste and can be used to monitor trash cans in an IoT environment. Integrating with a trained model using the Raspberry Pi 4 and TensorFlow Lite, the camera waste detecting module categorizes waste. LoRa focuses on studies on smart bins transmitting bin status to LoRa receivers utilizing frequencies at 915 MHz.

Many other studies on AI are still helping LPWAN and Short-Range networks for IoT applications shown in Table VI.

C. 6LowPAN

This section will discuss the research that uses 6LowPAN as a Short-Range Networks technology. So, the focus of this section is on some research focused on AI used in 6LowPAN to enhance IoT performance. The following are related research studies.

TABLE VI. AI - LORA TO ENHANCE IOT

References	Topic	AI Solution
[98]	Health Monitoring	LSTM Recurrent Neural Networks
[99], [100]	IoT devices	Deep Learning (Artificial Intelligence)
[92], [96], [101]–[107]	Enhancement to LoRa	Machine Learning, Deep Reinforcement Learning, Q-Learning, and Deep Learning
[95], [108]	Fingerprint Identification and localization	Deep Learning
[93], [94]	Prediction, Detection, and Estimation	Deep Learning and Machine Learning
[97]	Smart Waste Management	Deep Learning
[109]	Smart Irrigation	Machine Learning
[110]	Geolocation	Machine Learning
[111]	LoRaWAN Network	Machine Learning
[112]	Grape Leaf Diseases	Deep Learning

Gopika *et al.* [113] discuss the IPv6 protocol that uses Low Power Loss Network (RPL), which is the most widely used routing mechanism in supporting IoT. Existing RPL standards are the mechanism for utilizing the objective function in selecting the best parent by involving which single metric, expected transmissions, or the number of hops in computing static IoT applications. This study proposes a novel Fuzzification with Machine Learning (FML).

Kharche and Pawar [114] discuss that 6LoWPAN shapes traffic volume in IoT where service quality (QoS) is mandatory on sensor input. 6LoWPAN is surprisingly weak on interference since the physical and data layer links use the IEEE 802.15.4 standard in communications. There is interference in 6LoWPAN that affects the QoS regarding data loss rates, packet reception, and maintenance. This study proposes an algorithm for routing based on a deep neural network because it can offer solutions to solving problems by reducing interference and interference.

Maleh *et al.* [115] discuss that Particle swarm Optimisation (PSO), an easy and versatile optimization technique. PSO is used in making enhancement and developments in engine efficiency learning techniques. This study compares various ML techniques to perform intrusion detection on IoT components. The main problem is like a 6lowPAN IoT attack. by utilizing the Cooja IoT Simulator to produce attacks.

There are many more studies of 6LowPAN in enhancing the performance of IoT in its utilization with AI. Other studies are described in Table VII.

D. NB-IoT

In this section, the author will explain other research on LPWAN, namely NB-IoT by utilizing AI to enhance IoT performance. The following are related research studies.

TABLE VII. AI – 6LOWPAN TO ENHANCE IOT

References	Topic	AI Solution
[113]	Internet of Things applications	Machine Learning
[114], [116]	Enhancement to 6LowPAN	Deep Learning and Reinforcement Learning
[115]	Cyber Attacks Detection	Machine Learning
[117]	Security-Aware	Deep Learning
[118]	Early Fire Detection	Deep Learning

Liu *et al*. [119] discuss ML and NB-IoT in Support Vector Machine (SVM). This research focuses on developing smart stations with the aim of recognition. First, data in the form of voltage is sent to the host using NB-IoT. After that, in conducting the analysis, this study found that data in the form of electrical voltage and devices that can perform energy acquisition in similar areas have spatial and temporal correlation. Therefore, the SVM classification method is used to see the relationship between attributions to identify them.

Caso *et al.* [120] discuss that massive Machine Type Communications (mMTC), which has now become huge for NB-IoT, are expected to function in handling massive device connectivity reliably and efficiently. This study presents the analysis in the database. This study shows how procedures and performance Random Access (RA) can affect radio coverage, network, and operator configuration deployment to complete the simulation-based investigation. Thus, the study proposed the ML approach and demonstrated that the outcome of RA is predictable

Guo and Xiang [121] Discuss that the Evolved Packet System (EPS), which haNB-IoT architecture, can be expected as a paradigm in gaining energy-aware support for Large mMTC. However, with the number of devices experiencing a tremendous increase from IoT, there are current requirements such as low cost, energy-saving, and other things such as restrictions on NB-IoT technology. Until now, the standard opening allocation mechanism is still random in helping NB-IoT technology. So, this study develops a framework for optimizing the energy efficiency of the NB-IoT system. AI-based multi-Agents, etc.

After describing some of the existing research, the author feels it is insufficient. Table VIII will help present research focusing on AI in NB-IoT to enhance IoT performance.

TABLE VIII. AI – NB-IOT TO ENHANCE IOT

References	Topic	AI Solution
[119], [122]	Recognition and Prediction	Machine Learning
[120], [123]–[129]	Enhancement to NB-IoT	Machine Learning, Reinforcement Learning,, Deep Reinforcement Learning and Deep Learning
[121]	Energy Efficiency	Deep Reinforcement Learning
[130]	Farming Irrigation	Machine Learning
[131]	Device-to-Device (I-D2D)	Reinforcement Learning
[132]	Health Care	Intelligent System
[133], [134]	Access Control and Access Channel	Deep Learning, Deep Reinforcement Learning

E. Bluetooth

In this section, author will continue researching Short-Range Networks, namely Bluetooth that utilize AI to enhance IoT performance. This section focuses on Bluetooth and other relevant research. The following are related research studies:

Ok *et al.* [135] Discussing ICT technology that has been used in various areas in providing services by utilizing IoT. Utilizing location-based services utilizing beacons has several advantages, such as it can be used semi-permanently utilizing BLE. This study utilizes the advantages of BLE in concluding the beacon localization space. This study carried out deep neural network studies to show localization accuracy.

Zualkernan *et al.* [136] Discussion of recent technological advances in providing personalized experiences for customers, especially those related to the physical environment such as restaurants, retail stores, and cafes, still have their challenges. This study proposes BLE's pervasive environment and unattended ML to personalize customer visits to a café or coffee shop. As if in helping customers with automated table orders based on their preferences, leveraging the coffee maker (barista) interface in performing personalized interactions.

Shao and Nirjon [137] Discuss Deep implementation in The Image Beacon system that allows for emitting color images over long periods and utilizes a low-cost, low-power, and limited set of BLE memory. The study adopts a neural network image deep encoder to perform coding on the input image that is formed to get results to get a concise representation of the image. The study carried out partner development through a smartphone application, in one shooting app, and user requirements as input.

In its application, there is a lot of research on Bluetooth or BLE, which is a benchmark in utilizing AI to enhance IoT. Table IX presents several other studies related to AI on Bluetooth or BLE in enhancing IoT performance.

TABLE IX. AI – BLUETOOTH TO ENHANCE IOT

References	Topic	AI Solution
[135], [138]–[147]	Positioning, Localization, and Detection	Machine Learning and Deep Learning
[136]	Smart Cafes	Machine Learning
[137]	Image Storage and Broadcast	Deep Learning
[148]	Energy Efficiency	Q-Learning

F. NFC

This section still explaining about Short-Range Networks communication in IoT. This section focuses on NFC, which utilizes AI to enhance IoT. The following are related research studies:

Rodriguez *et al.* [149] The discussion of the deployment of a large number of devices on wireless sensors is a fundamental knowledge of the development of the IoT industry. Therefore, researchers must utilize hardware in making a sensing function with no or little hardware that needs to be added. The classification of this research uses single value decomposition (SVD). As NFC and wireless power transfer (WPT) are becoming the standard for smartphone features, this study looks at the freshness of drinks WPT/NFC technology-based sensing relevant to smartphones. After that, a circuit model was proposed and developed for the drink-coil interaction with several existing features to be classified, tested, analyzed, and tested.

Ali *et al.* [150] Discuss that monitoring skin care has become very important. This study develops a device for performing smart skincare that can harvest smartphone-based NFC energy and a battery-free approach. The device in this study consisted of two integrated sensors for ultraviolet (UV) measurements and skin moisture. This study conducted several experimental tests using different subjects indoors and outdoors. Studies are put into deep learning that utilizes ANN, which is used in predicting appropriate outcomes and calculating respective mean square error (MSE).

Then some other research that can be utilized in AI on NFC, which is used to enhance IoT performance, is presented in Table X.

TABLE X. AI – BLUETOOTH TO ENHANCE IOT

References	Topic	AI Solution
[149]	Detection	Machine Learning and Deep Learning
[151]	Controlled Remote Access	Machine Learning
[150]	Skincare Monitoring	Deep Learning

G. RFID

In this section, we are still discussing Short-Range Network communication in IoT, namely RFID, which can help IoT by utilizing AI, which will be presented in this section. The following are related research studies:

Cheng *et al.* [152] Explain that the core supporting technologies of IoT, namely RFID technology, can be quickly popularized in the logistics management field environment, industrial automation, intelligent transportation, and other similar things. This technology happens because they all have a definite and unique development due to fast data collection and efficiency. RFID is usually often used in the field of localization. The study aims at implementing the existing three-dimensional mechanism scheme based on RFID. In study performs mining what the characteristics of the data with DL and perform method implementation into the smart library scene

Yan *et al.* [153] Discuss that RFID is widespread in logistics and supply chain management because of its low cost. Various real-world problems, such as researchers, often need to benefit from many RFID readers to cover an extensive area. Several graphic-based solid RFID reader systems have been developed as anti-collision algorithms to overcome this problem. However, which of the advanced algorithms is the centralized algorithm? Graphs generated by a centralized algorithm in dense RFID systems are very difficult. This study proposes the MWISBAII anti-collision algorithm. This study also introduces ML into the proposed algorithm.

Sharif *et al.* [154] present an approach based on ML and RFID in sensing contamination of alcohol, soft drinks, alcohol, infant formula, etc. This study utilizes an inkjet sticker type printed on an ultra-high-frequency (UHF). This technology conducts sensing experiments to determine contamination. RFID tag antennas are affixed to contaminated food products using known contaminants. The study measured RSSI and the backscatter signal phase of the built-in RFID tag food items using the Tagformance Pro settings. Researchers utilize ML algorithms such as XGBoost for model training.

After getting some research on RFID by utilizing AI that can help IoT, Table XI presents several other related studies.

TABLE XI. AI – RFID TO ENHANCE IOT

References	Topic	AI Solution
[152]	Indoor Localization	Deep Learning
[153], [155]–[159]	Enhance RFID	Machine Learning and Deep Learning
[154]	Food Contamination Detection	Machine Learning

H. Cellular IoT

This last section will explain communication in a Short-Range Network, Cellular IoT, which utilizes AI to enhance IoT performance. The following are related research studies:

Savic *et al.* [160] explain that IoT devices in infrastructure have increased. This factor becomes a challenge for the management and security of IoT devices. Among them several proposals to overcome these problems, such as utilizing data-based methods rooted in DL. This study was carried out because of the large number of 5G waves in IoT connectivity and integrated DL-based anomaly detection (AD) in various fields. That can work for 3GPP mobile cellular IoT. The study proposes an (ADM-EDGE) autoencoder detection module in mobile core networks for IoT devices and (ADM-FOG) mobile core networks.

Sharma and Wang [161] Describe that concurrent access that still and rarely requests from MTC, based on existing contention RA as in Slotted ALOHA found severe Random Access Channel (RACH) problems, such as the occurrence of unwanted congestion on the cellular IoT networks. Therefore, the study proposes a distributed Q-learning approach in implementing a new MTC collaborative mechanism to address this issue. This technology allows finding unique RA slots for their transmissions.

Kim *et al.* [162] Described that IoT has been massive over the past few years. This technology happens because the environmental communication allocation scheme can help connect several IoT. So that a communication system is needed to support the IoT cellular network, this study proposes an optimization algorithm based on deep learning in solving resource allocation problems. Especially those in the uplink of the IoT cellular network, where each base station utilizes several sub-bands to help IoT. In particular, in maximizing the number of IoT users that must be achieved with low complexity, the study developed the CNN method sequentially and neatly in maximizing sub-band assignment and transmit power control.

Because there are other studies on Cellular IoT that utilize AI in enhancing IoT performance, it is presented again in Table XII to see related studies.

TABLE XII. AI – CELLULAR IOT TO ENHANCE IOT

References	Topic	AI Solution
[160]	Anomaly Detection	Deep Learning
[161], [163]	Enhance to Cellular IoT	Machine Learning and Q-Learning
[162]	Assignment and Power Control	Deep Learning
[164]	Spectrum sensing and allocation	Machine Learning

V. CONCLUSIONS

This study's systematic review of PRISMA focuses on AI used in LPWAN and Short-Range Networks to enhance IoT performance. The choice of the PRISMA method is because this method is very suitable for conducting systematic reviews. The first line is that the author searches for well-known research sources and gets 3784 papers. After that, the PRISMA steps are carried out to get a final paper of 79 suitable for this systematic review study. With several papers originating from China, then many papers from conferences, last year the papers researched a lot related to this was 2020-2021. In the selected paper, the author describes the derivatives of LPWAN technology and Short-Range Networks that have been widely studied, especially technologies such as; LPWAN in general, LoRa, Sigfox, NB-IoT, 6LowPan, Bluetooth, NFC, RFID, and Cellular IoT. After that, a detailed discussion of the papers focused on each technology. This systematic review is useful in searching for related research for further research in experiments or follow-up reviews. In the next review, other systematic approaches can be used or continue this review on AI technologies used in LPWAN or Short-Range Networks that have not been reviewed in enhancing IoT performance.

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