ML in WSN Using IoT for Smart Cities: A Survey

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1 Introduction

A smart city is an urban region that collects data from many areas using remote sensors, and Internet of Things (IoT) enabled technology to improve people's quality of life. Wireless sensor networks with low power and low data rates are utilized in smart city monitoring and control applications. In the Internet of Things, WSN nodes serve as the underlying technological backbone. The "things" in the Internet of Things are small embedded physical sensing devices (i.e., WSN nodes) that are connected to the internet to execute a specified task. Artificial intelligence (AI) and machine learning (ML), two new breakthrough techniques, are now emerging as the future of fully automated IoT applications [1]. Machine learning is a branch of artificial intelligence in which computer systems learn on their own by improving on previous experiences. Until 2013, a comprehensive study of machine learning algorithms was conducted. Because ML and IoT technologies are quickly evolving, the authors have expanded their survey chapter. Smart traffic monitoring, smart grids, smart waste management, smart agriculture, smart medical healthcare, and other IoT applications in smart cities are examples. Table 1 lists all of the significant abbreviations used in this chapter in complete form.

Truly automated operation, maximum network lifetime, energy efficiency, quality of service (QoS), cross-layer optimization, high bandwidth demand, sensor data processing, cloud computing, communication protocol design, and other issues plague WSN-based IoT (WSN-IoT). The industrial Internet of Things (IIoT) or industry 4.0 is now the most significant transformation in smart industries, smart manufacturing, automobiles, smart cities, and medical healthcare. Various large corporations, such as Microsoft, Google, and Amazon, are developing AI and

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Table 1 Shows an alphabetical list of abbreviations

Acronym	Description
5G	5th Generation Cellular Networks
6G	6th Generation Cellular Networks
AMQP	Advanced Message Queuing Protocol
ANN	Artificial Neural networks
BLE	Bluetooth Low Energy
CoAP	Constrained Application Protocol
DDS	Data Distribution Service
DL	Deep Learning
DT	Decision Tree
IoT	Internet of Things
k-NN	K Nearest Neighbourhood
LDA	Linear Discriminant Analysis
LoRaWAN	Long Ranged Wide Area Network
LTE	Long Term Evolution
MAC	Medium Access Control
MLMDP	Machine Learning Markov Decision Process
MLP	Multi-Layer Perceptron
MQTT	Message Query Telemetry Transport
NB-IoT	Narrowband IoT
PCA	Principle Component Analysis
QoS	Quality of Service
RL	Reinforcement Learning
RFID	Radio frequency Identification
SARSA	State-Action-Reward-State-Acton
SVM	Support Vector Machines
TCP	Transmission Control Protocol
UDP	User Datagram protocol
WSN-IoT	WSN based IoT
WSN	Wireless Sensor Networks

machine learning-based algorithms for sophisticated IoT applications in smart cities across the world.

Machine learning may be used in WSN-IoT for dynamic routing table updates, node localization in mobile WSN-IoT nodes, identifying and separating defective nodes for network optimization, and predicting the quantity of energy harvested in energy harvesting WSNs (EH-WSN). The writers of this study attempted to answer the following research questions: Why are machine learning techniques employed in the WSN-IoT? What are the advantages of utilizing machine learning over traditional optimization approaches in WSN-IoT? Why is the smart city a common IoT application use case?

Smart cities may now utilize data to better control traffic, decrease pollution, and make better use of infrastructure thanks to the Internet of Things [2]. The benefits of applying machine learning in conventional WSN-IoT are as follows:

In most cases, WSNs are deployed in a constantly changing environment. As a result, a fully automated IoT scenario should expect self-adaptation to the new environment. Unknown parameter monitoring, such as temperature measurement in a glacier or volcano monitoring, necessitates automatic network architecture and configuration adjustments. In WSN-IoT, there aren't any reliable mathematical models for the unknown parameters. Because WSN-IoT works with a lot of sensor data, the correlation between multiple data sets might be a big problem. WSN integration with IoT via cloud-based services for improved monitoring and control.

In the WSN-IoT, future predictions and actions are conceivable.

From millions of sensor nodes, the Internet of Things creates a tremendous amount of data. Data drive machine learning, which creates usable knowledge from prior data. Machine learning makes use of historical IoT data to uncover hidden patterns and creates models that may be used to forecast future behaviour and occurrences. Due to the resource constraints of WSN-IoT, there are several restrictions to executing ML-based inferences on IoT nodes, such as:

As more data are processed, a greater number of computations are required, increasing computation complexity.

Extra energy consumption.

Complex procedures and multi-domain expert programmers are required to train WSN-IoT nodes for multiple ML algorithms.

The contributions of this survey chapter in the realm of WSN-IoT are as follows:

The use of machine learning techniques as an optimal solution for classic WSN-IoT issues in smart cities is presented in this chapter. The WSN-IoT framework's design recommendations based on AI and ML have been presented [3]. For ML engineers and data scientists, an in-depth literature study of WSN-IoT in smart cities is provided in detail.

2 WSN-Based IoT

Figure 1 depicts the functioning of WSN-IoT in a smart city. The WSN nodes are used in smart city applications including traffic monitoring, creating smart grids, remote health care monitoring, smart agriculture, and industrial applications. A smart city's IoT-WSN node's job is to continually monitor and manage physical quantities including temperature, humidity, pressure, acceleration, and so on. These sensor nodes' main job is to collect data and deliver it to the main WSN-IoT gateway node. The data are transmitted to the cloud server from the gateway node [4]. Cloud computing takes occur in the IoT cloud. Remote servers, user mobile

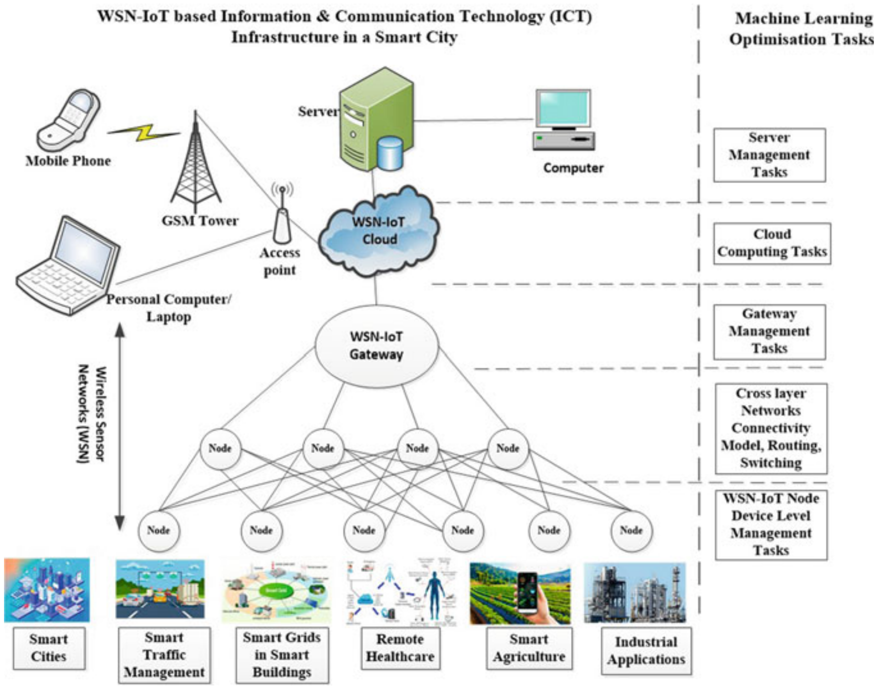

Fig. 1 WSN-IoT in a smart city utilizing ML

phones, computers, mobile phone towers, and other IoT cloud components are all directly connected. IoT and machine learning operations need a significant quantity of data processing and memory. As a result, the IoT cloud server is built as a high-performance, high-processing computer with a large storage capacity. WSN end nodes, on the other hand, have limited computational capabilities, limited storage, and a finite non-rechargeable battery power source. The maximum data rate for WSN-IoT end nodes based on the IEEE 802.15.4 standard is 250 kbps. End nodes of WSN-IoT are powered by two AA-size batteries (1.5 V, 1000 mAh), while the gateway is supplied by the mains. Machine learning algorithms may be deployed from the cloud to the WSN-IoT node device level for autonomous operation. The sensor data are sent to the cloud server via the IoT device [5]. The user may monitor and manage the application from the IoT cloud using a smartphone, laptop, or desktop PC, as well as a personal digital assistant. Many prominent cloud service providers now provide a free, but restricted, quantity of sensor data storage in their cloud storage. For example, Mathworks Incorporation's Microsoft Azure IoT, Amazon Web Service (AWS), Google cloud platform, Cisco IoT cloud connect, IBM Watson IoT, and Thing talk IoT.

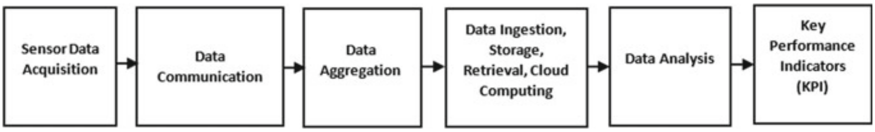

Fig. 2 A typical WSN-IoT application's data flow

3 Preliminaries in ML for WSN-IoT

ML is a branch of artificial intelligence that allows computers to learn and develop on their own without having to be explicitly programmed. Its goal is to create new computer programs that can access data and learn on their own (Figs. 2 and 3).

I. **Training Process**: First and foremost, data are obtained through a certain application. These raw data are used to extract the characteristics. If the data includes picture data, for example, the colours, pixels, brightness, and contrast of the whole database of images are extracted. The features are then categorized according to the machine learning process's requirements [6]. In order to learn or enhance the fundamental starting algorithms, certain training examples are now applied to them. As a result, algorithms are taught and optimized based on data patterns.

II. **Testing Process**: The next stage is to put this well-trained WSN to work in a real-world application. In the actual world, unknown data are used as input and characteristics are retrieved [7]. These retrieved characteristics are fed into an algorithm that has previously been trained. The trained algorithm's output is categorized as data predictions.

III. **Actions of the WSN**: Finally, the WSN determines the necessary actions based on expected output data.

4 Open Research Problems in WSN-IoT That ML Techniques Can Solve

The following are open research topics in WSN-IoT that can be solved using machine learning approaches.

5 Localization of IoT Nodes

The current position identification of a sensor node in a WSN situation is referred to as node localization. Path planning is a critical stage in mobile WSN nodes. Because all nodes are split (classified) into range-based and range-free nodes, node localization is considered a classification challenge. For node localization as a classification issue,

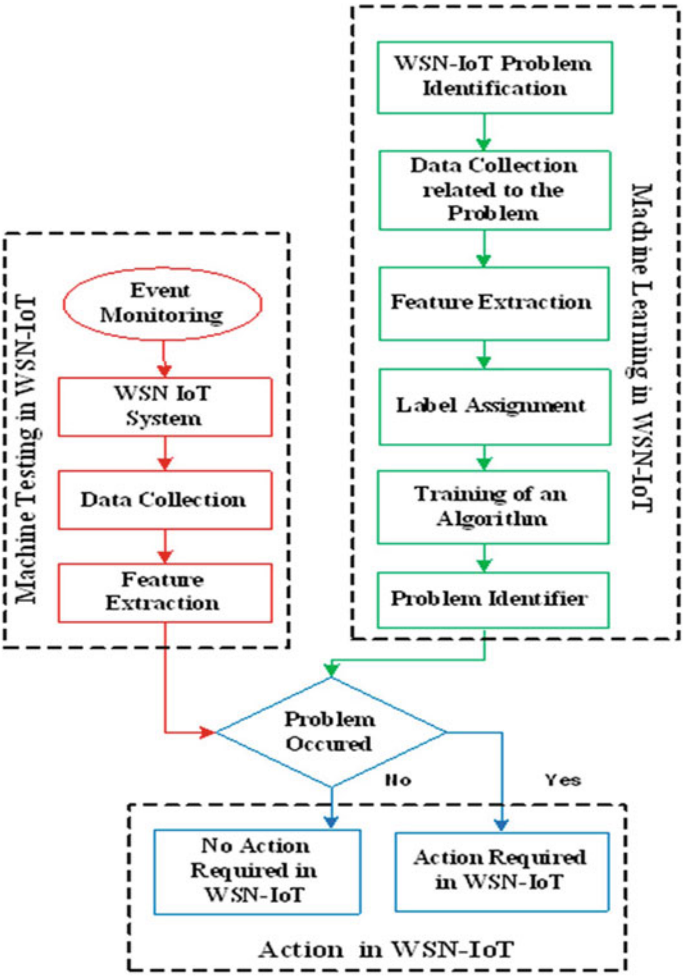

Fig. 3 Machine learning process flowchart in WSN-IoT

several ML algorithms such as SVM, K-NN, and RL-based approaches (Q-learning, SARSA) are employed in WSN-IoT.

6 Coverage and Connectivity of IoT Nodes

The sensing coverage in a WSN scenario is the field of interest (FOI), which is defined as the area covered by at least one sensor node. As a result, the best location for sensor nodes is a design challenge [8]. The connection between neighbour nodes should be suitable to enhance the WSN lifespan.

7 Issues of Routing Layer

Routing is the process of delivering data packets from one node to another via intermediary nodes [9]. Long routing tables, which contain the source and destination addresses of all packets in the network, are maintained by gateway nodes during the routing process [10]. The end nodes of a WSN send the detected data to the main gateway node. In a WSN network, if the routing path is excessively lengthy, a lot of energy is lost. As a result, smart routing algorithms must be carefully developed to identify the best paths between end nodes and gateway nodes [11]. WSN uses a variety of machine learning approaches to identify the best path, including decision trees, random forests, ANN, SVM, and Bayesian learning [12].

8 Issues with the MAC Layer

WSN's media accessing method is controlled by the MAC layer. In WSN, the sensor MAC (SMAC) protocol is commonly employed [13]. In WSN, methods based on reinforcement learning (RL) are utilized to build MAC protocols. In sensor networks, RL-MAC methods manage sleep, waking, transmission, and reception [14].

9 Aggregation of Sensor Data

Thousands of tiny sensor nodes are distributed in a smart city to measure the same physical quantity, such as temperature, humidity, light, CO_2 gases, and so on. Several sensors might send the same data to the gateway. The gateway struggles to process such a big volume of data. As a result, in WSNs for smart city applications, sensor data aggregation is critical. Data aggregation is the process of gathering and combining valuable data from many sources [15]. Data redundancy and accuracy are increased as a result of this procedure. Data aggregation reduces the power consumption of WSN nodes, extending the network's lifespan. Data aggregation can benefit from machine learning [16]. The data from the cluster head are aggregated and sent to the base station by the cluster [17]. For data aggregation tasks in WSN-IoT, machine learning approaches based on artificial neural networks (ANN) and quality (Q)-learning algorithms are effective [18].

10 Target Detection and Event Monitoring

WSNs are used in smart city applications to monitor events and detect targets, such as intrusion detection and traffic tracking [19]. Node failure, target recovery, and sensing node tracking latency are all necessary for a WSN. For event monitoring and target tracking in WSNs, several ML approaches such as Bayesian, Q learning, and genetic algorithms are utilized [20]. Using machine learning techniques in WSNs can help recognize an event or target from complicated image sensor data.

11 Harvesting of Energy

The process of gathering environmental energy from the sun, wind, tides, radio waves, and other sources and converting it into electrical energy is known as energy harvesting [21]. The overall goal of energy harvesting is to conserve our finite supply of fossil fuels (coal, oil and gases). Energy harvesting, on the other hand, may be utilized in smart city applications to achieve maximum network lifespan in rechargeable battery-based WSN-IoT nodes [22]. Furthermore, machine learning techniques are employed in energy harvesting WSN-IoT activities for predicting future available energy [23]. For energy harvesting applications, machine learning methods such as regression and reinforcement learning approaches (Q-learning) are applicable. With rechargeable battery-based WSNs, solar energy, radio frequency waves, and wind energy are typically employed. Traditional WSN-IoT activities such as harvested energy forecast and battery power management can benefit from the use of machine learning techniques.

12 Processing of Node Query

End nodes, cluster heads, and gateway nodes all conduct different sorts of queries in WSNs, including sensor data aggregation, routing pathways, synchronization and control activities, packet delivery, and so on [24]. For sensor data queries in WSN, k-nearest neighbourhood-based ML methods are employed.

13 Our ML Techniques in WSN-IoT Survey Report

We conducted this chapter by looking up machine learning in WSN-IoT for smart cities on numerous websites, journals, magazines, and research papers [25]. We found several articles accessible from 2010 to 2021 by searching the internet for ML methods tackling WSN-IoT issues [26]. It illustrates the percentage contribution of category-wise ML algorithms solving WSN-IoT problems. The graphical depiction of main ML algorithms in WSN-IoT is shown in Fig. 4.

Figure 5 depicts a brief overview and simple graphical depiction of the key machine learning techniques utilized in WSN-IoT.

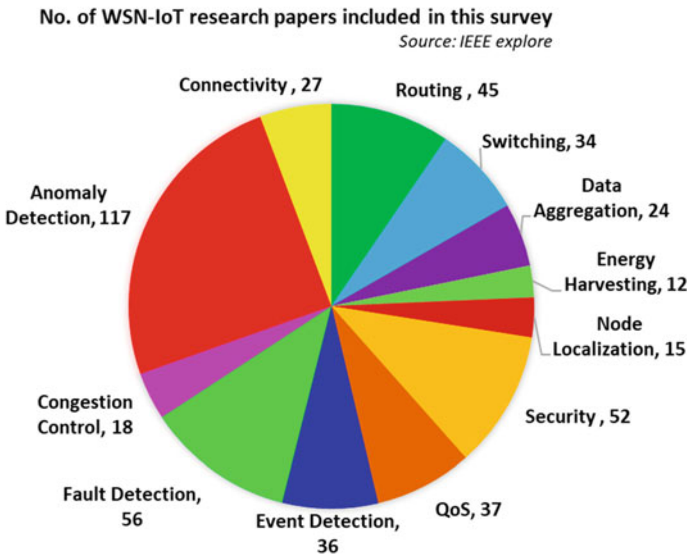

Fig. 4 Shows the research articles on WSN-IoT technologies. *Source* IEEE explore

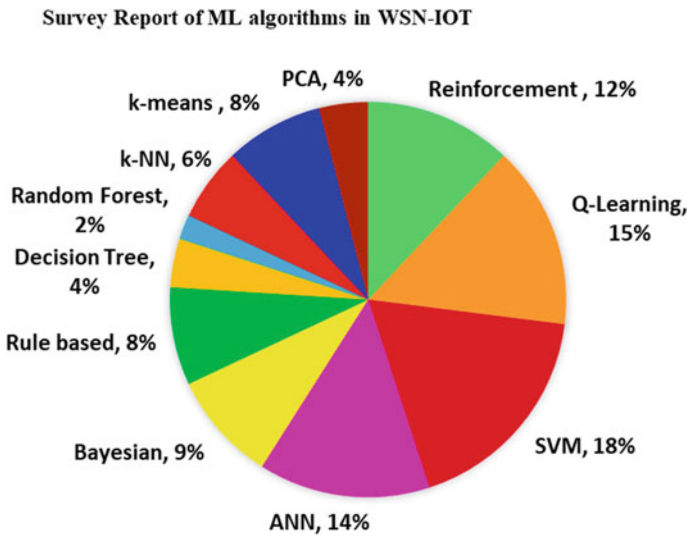

Fig. 5 Graphical representation of major ML algorithms used in WSN-IoT. *Source* IEEE explore

Figure 6 depicts the prevalence of RL, supervised, and unsupervised learning algorithms in WSN-IoT in a simple graphical depiction.

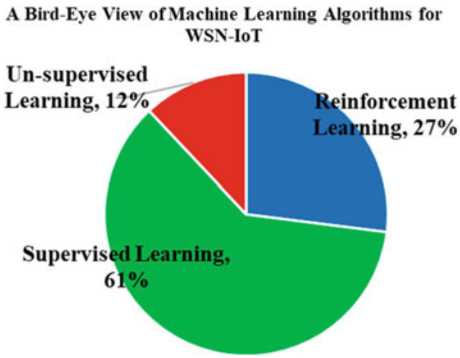

Fig. 6 Graphical representation of RL, supervised and unsupervised learning algorithms in WSN-IoT. *Source* IEEE explore

14 Conclusions and the Next Steps

We discussed several machine learning methods in WSN-IoT for smart city applications in this chapter. We conducted a thorough assessment of ML methods in WSN-IoT for smart city issues in the chapter. According to the results of this poll, supervised learning algorithms were employed the most, with 61%, compared to RL with 27% and unsupervised with just 12%. Because machine learning algorithms are so diverse and strong, they can be utilized for many tasks in WSN-IoT in smart cities. In WSN-IoT, the sophisticated SVM algorithm, for example, may be utilized for classification and regression applications. A more powerful and complicated algorithm will develop in the future, reducing the need for human involvement. Machine learning techniques will be used in the upcoming IoT-based smart city solution. The heart stroke rehabilitation system in smart health care, for example, employs LDA, MLP, and SVM algorithms. Ultra-dense cellular IoT networks based on high-performance machine learning algorithms will be used in next-generation smart cities.

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