



Enhancing Routing, and Data Aggregation in WSNs Using Artificial Intelligence: A Survey

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Abstract:

Wireless Sensor Networks (WSNs) are widely used in many applications such as smart cities, agriculture, healthcare, and environmental monitoring. However, WSNs face several challenges, including limited energy, weak processing power, routing problems, data redundancy, and poor scalability in large networks. Artificial Intelligence (AI) has emerged as a promising solution to improve the performance and efficiency of WSNs.

This survey paper reviews how AI techniques are used to enhance routing, data aggregation, and scalability in WSNs. It discusses different AI methods such as machine learning, deep learning, reinforcement learning, and fuzzy logic, and explains how they help optimize data transmission, reduce energy consumption, and improve network lifetime. The paper also highlights real-world applications, key challenges, and future research directions in AI-based WSN systems.

This study aims to provide researchers and practitioners with a clear and simple understanding of the role of AI in improving WSN performance and supporting the development of more intelligent and efficient sensor networks.

Keywords: Wireless Sensor Networks (WSNs), routing, Artificial Intelligence (AI), data aggregation.

المخلص:

تُظهر هذه الدراسة أن بناء شبكة استشعار لاسلكية فعالة يتطلب اختيار أفضل سيناريو للنشر والتركيز على عدة عوامل مهمة. أهم هذه العوامل هو إطالة عمر الشبكة من خلال تمكين عقد الاستشعار من العمل لأطول فترة ممكنة. يكتسب هذا الأمر أهمية خاصة نظرًا لأن شبكات الاستشعار اللاسلكية غالبًا ما تُنشر في مناطق نائية ويصعب الوصول إليها.

لتحقيق ذلك، يجب تحديد معايير تصميم واضحة، والحد من نقاط ضعف النظام باستخدام تقنيات الذكاء الاصطناعي المناسبة. يمكن لهذه الخوارزميات تحسين أداء الشبكة، لا سيما في التوجيه وتجميع البيانات، مع توفير الطاقة.

تُستخدم شبكات الاستشعار اللاسلكية في العديد من التطبيقات اليومية، ولكل تطبيق متطلباته الخاصة. على سبيل المثال، في الزراعة، قد لا يكون أمن البيانات مصدر قلق رئيسي، ولكن دقة البيانات وكفاءة استهلاك الطاقة أمران بالغ الأهمية. في مثل هذه الحالات، تُستخدم خوارزميات الذكاء الاصطناعي لتقليل استهلاك الطاقة أثناء نقل البيانات مع الحفاظ على موثوقية البيانات ودقتها.

الكلمات المفتاحية: شبكات الاستشعار اللاسلكية (WSNs)، التوجيه، الذكاء الاصطناعي (AI)، تجميع البيانات، قابلية التوسع.

Introduction

Wireless Sensor Networks (WSNs) are an important technology used in many applications. many WSN nodes are low-cost and require minimal infrastructure, making deployment feasible even in remote or wide-area environments, WSNs provide real-time monitoring and automated data collection, allowing prompt responses to environmental changes or system events [1], WSN often struggle with limited resources and dynamic network conditions. With the growing need for efficient data management in these networks, it is more important than ever to understand and enhance these techniques. [2]. The sensor nodes of a WSN are autonomous, dispersed devices that gather and direct data to a central hub, or “Base Station”, using wireless connections without any central coordinator [3]. This allows real-time monitoring and helps systems make decisions with less human intervention. In a WSN, information is relayed from one node to the next until it reaches the base station. Most nodes may be reliably expected to operate for the duration of their batteries. These strategies encompass reducing energy

consumption, minimizing latency, load balancing, clustering, efficient data aggregation, and curtailing data transmission delays [3,6].

However, WSNs face many challenges because sensor nodes have limited energy, memory, processing power, and communication ability. One of the biggest problems is energy consumption, since most nodes depend on batteries. Therefore, it is very important to reduce energy usage in order to extend the network lifetime. Another challenge is scalability. When the number of nodes increases, it becomes difficult to manage routing and maintain good network performance. In addition, WSNs generate large amounts of data that must be processed and managed efficiently.

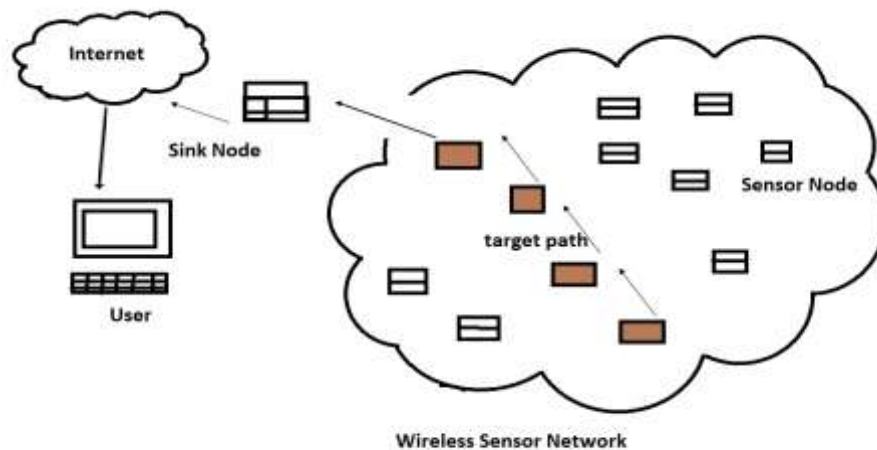


Figure 1: Wireless Sensor Network.

Many issues plaguing WSNs can be easily overcome and performance can be greatly improved by utilizing machine learning, some ways in which ML is used to extend the lifespan of WSNs include the following: Anticipating the volume of energy that can be collected during a given time slot, which is necessary to increase the longevity of WSNs, ML-based localization that actually works, Using ML to identify the faulty links, Using ML to decrease the dimensionality of data at the level of the sensor [3]. Developments in AI methodologies such as machine learning, deep learning, and reinforcement learning have led to rapid advancement in WSNs [4].

To solve these problems, researchers have started using Artificial Intelligence (AI). AI helps improve WSNs by making better decisions, optimizing network operations, and saving energy. Techniques such as machine learning, deep learning, and reinforcement learning can support adaptive routing, threat detection, and energy management.

Deep learning algorithms (DL) have the capability to acquire knowledge from the data obtained through sensors and utilize this information to generate predictions or make informed judgments. In healthcare applications, WSN can facilitate the collection and transmission of medical data collected from various sensors, which can then be analyzed using the deep learning model, a custom convolutional neural network [4].

Explainable AI, digital twin technologies, and wireless sensor networks together as a single concept bring a new level of understanding of the interactions with complex systems. This concept not only enhances information decision-making through increased transparency and trust, but also facilitates better operational decisions across various industries. Over time, the specific and combined possibilities will be further enhanced, and a range of additional applications will be developed [4].

ML algorithms, when used in WSN create innovative solutions that address WSN challenges. Intelligent algorithms have the potential to contribute to more efficient, adaptive, and smart sensor networks. Intelligent resource management schemes enhance the efficiency of WSN by optimizing the utilization of the network's available resources [5].

AI techniques such as machine learning (ML), deep learning (DL), and optimization algorithms are useful tools to overcome these challenges. Machine learning allows the network to learn from past data and predict future

behavior. This helps in better resource management, fault detection, and energy saving. For example, ML can predict traffic patterns or node failures, so the network can adjust its operation and increase its lifetime.

Also, AI-based optimization algorithms such as genetic algorithms and particle swarm optimization are used to improve routing and sensor placement. These methods help find the best paths for data transmission while reducing energy consumption and maintaining good performance. This is very important because energy-efficient routing directly affects the lifetime of the network.

AI-driven protocols are capable of making time-optimal decisions through experience-based adaptation, thereby continuously refining energy management strategies. This enables efficient distribution of energy-intensive tasks, such as data transmission and aggregation, with respect to the overall lifetime of the network [7].

Problem Statement:

Although Wireless Sensor Networks have improved data collection and monitoring in many fields, they still face serious challenges that limit their long-term use. The main problems include energy consumption, network lifetime, Data Aggregation, and data fusion. Traditional methods are often not enough, especially in large, dynamic, or resource-limited environments.

One major challenge is maintaining network performance while ensuring long network lifetime. When sensor nodes lose energy or stop working, the network structure changes and performance decreases. This leads to loss of data accuracy and incomplete monitoring. Another challenge is data fusion, which means combining and processing data from many sensor nodes. This process must reduce redundant data and improve accuracy. Traditional methods are usually not flexible or adaptive enough to deal with large and real-time data streams.

Energy consumption is one of the most critical issues in WSNs. Since most sensor nodes use batteries, energy loss directly reduces the network lifetime. Therefore, efficient energy management is necessary to avoid frequent maintenance or battery replacement, especially in remote areas. Many existing energy-saving methods cannot adapt well to changing network conditions, which causes inefficient energy use and shorter network lifetime.

This paper aims to address these problems by studying how Artificial Intelligence can be used in WSNs. AI methods such as machine learning, deep learning, and optimization algorithms can provide smarter and more adaptive solutions. These methods can help reduce energy consumption, extend network lifetime, and improve data fusion. By using AI, WSNs can become more autonomous, self-adaptive, and able to respond to environmental changes in real time, which improves overall performance and reliability.

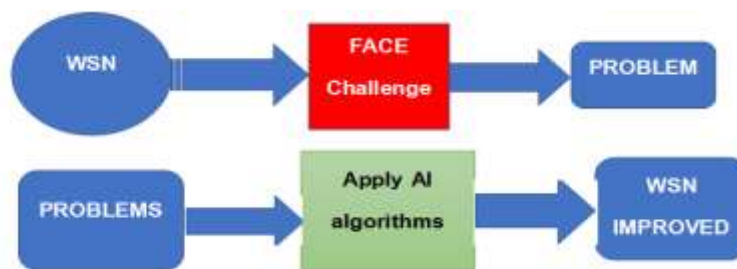


Figure 2: Wireless Sensor Network.

2- AI Techniques in WSNs

Artificial Intelligence (AI) has become a useful tool to solve many problems in Wireless Sensor Networks (WSNs). Different AI techniques, such as machine learning (ML), deep learning (DL), reinforcement learning (RL), and optimization algorithms, are used to improve different parts of WSNs. These methods help the network make better and smarter decisions [1,3].

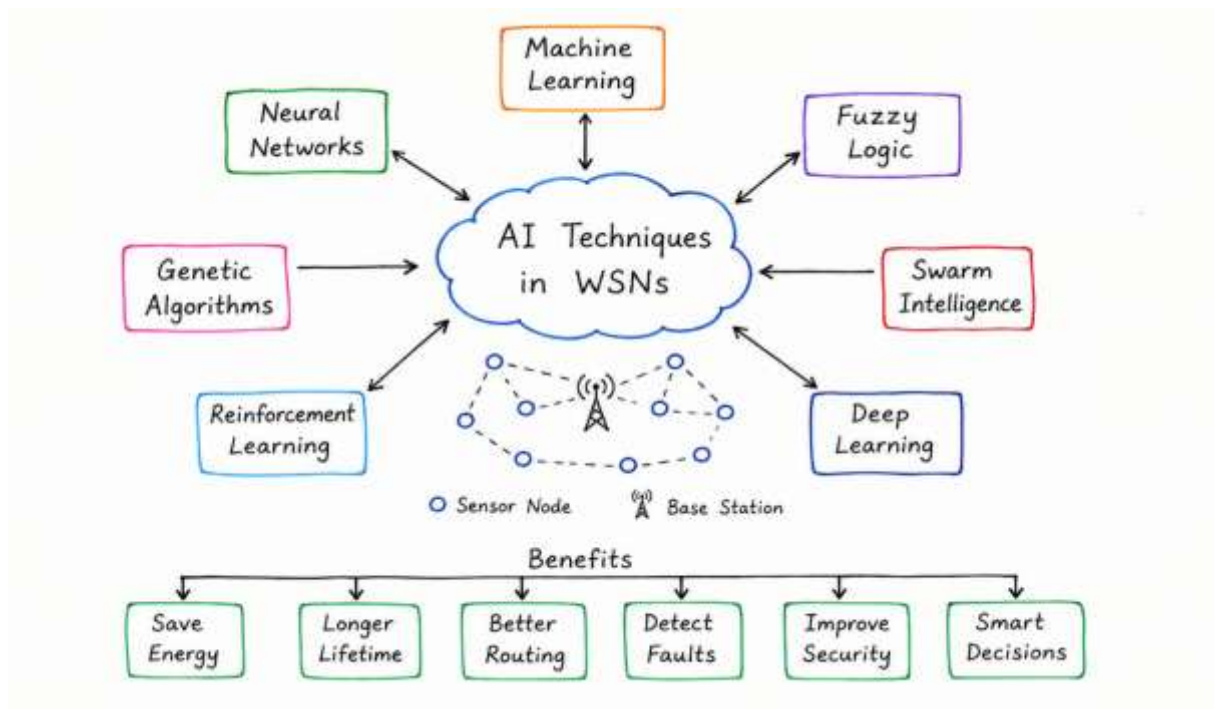


Figure 3: AI techniques in WSNs

2.1 Machine Learning (ML)

Machine Learning (ML) is a part of AI algorithms that allows WSNs to learn from past data and improve decisions without direct programming. In WSNs, ML is mainly used for [3,6]:

- **Energy Management:** ML models can predict network traffic and control node sleep times, so nodes use energy only when needed. By learning from previous behavior, the network can adjust its operation to reduce energy consumption.
- **Anomaly Detection:** ML algorithms, such as Support Vector Machines (SVM) and decision trees, are used to detect abnormal behavior, like unusual data transmission or node failures. This helps detect problems early and increases network reliability and lifetime.
- **Data Prediction and Compression:** ML models can predict future sensor values, so fewer data need to be transmitted while keeping acceptable accuracy. This reduces communication cost and extends network operation time.

2.1.1 Anomaly Detection

In WSNs, detecting unusual behavior or faulty nodes is very important to maintain performance and data accuracy. ML-based anomaly detection works by finding differences from normal behavior, which may indicate faults, attacks, or node failures. Algorithms such as SVM, k-Nearest Neighbors (k-NN), and Random Forest are commonly used [6].

For example, in an environmental monitoring system, an ML model may detect unexpected temperature values from some nodes, which could mean hardware problems or sudden environmental changes. By learning from historical data, the system can decide whether the behavior is normal or abnormal and take action.

2.1.2 Pattern Recognition

Pattern recognition is another important use of ML in WSNs. ML models can find patterns in sensor data and detect important events or behaviors. For example, in smart city systems, ML models such as Convolutional Neural Networks (CNNs) can learn traffic patterns from sensor data and help predict traffic congestion or suggest alternative routes [6].

2.1.3 Predictive Maintenance

In WSNs, sensor nodes are often placed in remote or hard-to-reach areas, which makes regular maintenance difficult. ML can be used for predictive maintenance, where the system predicts possible node failures before they happen.

For example, ML models such as Neural Networks and Recurrent Neural Networks (RNNs) can analyze performance data over time to predict battery depletion or hardware failure. When these risks are detected early, the system can alert operators to repair or replace the node, reducing downtime and data loss.

Predictive maintenance reduces operational costs, extends network lifetime, and improves overall reliability.

2.2 Deep Learning (DL)

Deep Learning (DL) is a type of ML that uses neural networks with many layers to extract complex features from large datasets. In WSNs, DL is used in several areas [6,10,12]:

- **Data Fusion and Processing:** DL models such as CNNs and RNNs can combine and analyze data from multiple sensors, reduce redundancy, and improve accuracy. This is very useful in applications like environmental monitoring where large amounts of real-time data are generated.
- **Event Detection:** DL models can detect complex events by learning patterns in sensor data. For example, in smart cities, DL can monitor traffic flow or detect problems in infrastructure.
- **Fault Prediction:** DL models can predict possible node failures by analyzing past data and finding patterns that appear before faults.

2.2.1 Processing Large Datasets

WSNs produce large amounts of data from many sensors, which is difficult to handle using traditional methods. DL algorithms, especially Deep Neural Networks (DNNs), can automatically extract useful features from raw data without heavy preprocessing. This makes them suitable for handling large and complex datasets in WSNs. For example, in environmental monitoring, DL models can analyze data from many sensors measuring temperature, humidity, and air quality to provide useful information. By using multi-layer neural networks, DL can capture complex relationships in the data and improve analysis accuracy.

2.2.2 Improving Data Accuracy

One of the main advantages of DL in WSNs is improving data accuracy. Traditional methods may not handle noise and variability in sensor data well, which can cause errors. DL models can learn from large labeled datasets and recognize both normal and abnormal patterns.

For example, in smart healthcare systems, DL can analyze physiological data from wearable sensors. After training on healthy and unhealthy data patterns, the model can detect critical conditions in real time and send alerts.

Also, CNNs can process multi-dimensional data, such as images or video, improving event detection and classification in applications like security monitoring and traffic analysis.

2.2.3 Enabling Real-Time Decision-Making

Real-time decision-making is very important in many WSN applications, especially in dynamic environments. DL models can work in real time, allowing WSNs to analyze incoming data and make immediate decisions.

For example, in smart cities, DL can analyze traffic data in real time to predict congestion and adjust traffic signals automatically. In disaster management, DL can analyze environmental data to detect dangerous conditions, such as floods or gas leaks, and trigger alerts or responses.

DL models can also adapt over time as data patterns change, which helps WSNs remain effective in changing environments.

2.3 Reinforcement Learning (RL)

Reinforcement Learning (RL) is an AI method where an agent learns by interacting with the environment and receiving rewards or penalties. In WSNs, RL is used in many adaptive processes [9,24]:

- **Routing Optimization:** RL algorithms like Q-learning can adjust routing paths based on current network conditions. The agent learns the best routes by considering traffic, node availability, and energy levels, which helps reduce energy consumption while keeping good communication [14].
- **Resource Allocation:** RL can dynamically allocate resources such as bandwidth and transmission power based on real-time needs, ensuring efficient resource use and acceptable quality of service.

RL is very useful in WSNs because it allows the network to learn from experience and improve its performance over time.

2.3.1 Dynamic Routing

Dynamic routing is important in WSNs because node availability, network topology, and traffic load change frequently. Traditional routing methods may not adapt well to these changes [21].

RL algorithms such as Q-learning and Deep Q-Networks (DQN) can create smart routing strategies that learn the best data paths based on real-time conditions. Each node acts as an agent and receives rewards based on successful data delivery, low energy use, and low delay.

For example, if a node sends data successfully with low energy consumption, it receives a positive reward. If the transmission fails or causes high delay, it receives a negative reward. Over time, the agent learns better routing strategies that balance energy efficiency and data delivery.

RL can also quickly adapt to node failures or congestion, which improves network reliability and performance.

2.3.2 Energy Management

Energy management is a major concern in WSNs because sensor nodes use batteries. RL can help develop energy-aware strategies that reduce energy use while keeping network performance acceptable [16].

RL can control node states such as sleep, idle, and active modes. Using methods like Actor-Critic algorithms, the network can learn when to save energy and when to transmit data.

For example, an RL agent can learn when to put nodes into sleep mode and when to wake them for data collection. Rewards are given based on energy savings and successful data delivery. Over time, the system finds a balance between energy conservation and responsiveness.

RL also supports adaptive duty cycling, where nodes adjust their wake-sleep schedules based on real-time traffic and data needs, which helps extend network lifetime.

2.4 Optimization Algorithms

Optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are used to solve complex problems in WSNs. These methods are applied in:

- **Energy-Efficient Routing:** These algorithms find routes that minimize energy use and delay by simulating natural behaviors such as evolution or swarm movement [16].
- **Sensor Placement:** Optimization methods help decide the best positions for sensor nodes to ensure good coverage and low energy use, especially in large networks.
- **Cluster Head Selection:** In clustered WSNs, optimization techniques help choose the best nodes to act as cluster heads, balancing energy use and extending network lifetime.

2.4.1 Genetic Algorithms (GA)

Genetic Algorithms (GA) are inspired by natural selection and evolution. They are useful for solving complex optimization problems in WSNs [7,10].

- **Resource Allocation:** GAs can optimize how bandwidth, energy, and processing power are distributed among nodes. By evolving solutions through selection, crossover, and mutation, GAs can find good strategies that improve network performance.
- **Sensor Placement:** GAs can determine the best sensor locations to maximize coverage and minimize energy use and cost. Fitness functions evaluate coverage, node distance, and energy efficiency to reach optimal solutions.

2.4.2 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is inspired by the behavior of birds and fish. It is simple and effective for optimization in WSNs[7,10].

- **Network Topology Control:** PSO can optimize network structure by adjusting node positions and communication links to improve connectivity and reduce energy use.
- **Energy-Efficient Routing:** PSO can find efficient routing paths by treating each path as a particle and evaluating energy use, delay, and data reliability, leading to adaptive routing strategies.

2.4.3 Other AI-Based Optimization Techniques

In addition to GA and PSO, other AI-based optimization methods are also used:

- **Ant Colony Optimization (ACO):** Inspired by ants' behavior, ACO is effective for routing and resource allocation. It adjusts routes dynamically based on network feedback.
- **Simulated Annealing (SA):** SA is a probabilistic method used to optimize network configurations such as sensor placement and topology by exploring different solutions and avoiding local optima.
- **Tabu Search:** This method uses memory to avoid repeating previous solutions and is useful for optimizing energy use while maintaining coverage and connectivity.

N	AI Techniques	WSN challengers
1	Machine Learning (ML)	• Energy Management • Anomaly Detection • Data Prediction and Compression
2	Deep Learning (DL)	• Data Fusion and Processing • Event Detection • Fault Prediction:
3	Reinforcement Learning (RL)	• Routing Optimization • Resource Allocation
4	Optimization Algorithms	• Energy-Efficient Routing • Sensor Placement • Cluster Head Selection

Table 1: AI Techniques VS WSN challengers

3. Applications of AI in WSNs

Artificial Intelligence (AI) is increasingly used in Wireless Sensor Networks (WSNs) in many fields, and this has led to better efficiency, reliability, and adaptability. This section presents some real-world examples that show how AI techniques have been successfully applied in WSN applications [18],[19].



Figure 4: Applications of WSNs

3.1 Smart Agriculture

In precision agriculture, WSNs with AI algorithms are used to monitor soil conditions, crop health, and environmental factors in real time. For example, researchers have used Machine Learning models to analyze data from soil moisture sensors and weather stations. Based on this data, the system predicts the best irrigation times, which helps reduce water usage and increase crop production. WSN with AI to improve irrigation in vineyards. The system used historical data and real-time sensor readings to predict water needs. As a result, water consumption was reduced by about 30%, and grape quality improved due to better irrigation management [23].

3.2 Environmental Monitoring

WSNs are widely used in environmental monitoring to measure air quality, water quality, and other environmental factors. AI techniques, especially Deep Learning, are used to analyze the large amount of data produced by these networks and provide useful information about environmental changes. WSN was deployed to monitor air pollution. Deep Learning algorithms were applied to the sensor data to identify pollution sources and predict pollution levels in real time. This helped city authorities take timely actions and improve air quality [27].

3.3 Smart Cities

In smart cities, AI-based WSNs play an important role in managing urban services such as traffic control, energy use, and public safety. Reinforcement Learning is often used to optimize traffic signal timing based on real-time data collected from sensors. A smart traffic system uses a WSN with Reinforcement Learning algorithms to control traffic lights. The system adjusts signal timings based on current traffic conditions, which led to a reduction of about 20% in traffic congestion and a noticeable decrease in vehicle emissions [28].

3.4 Healthcare Monitoring

In healthcare, wearable sensor networks use AI to continuously monitor patient health. Machine Learning models analyze physiological data and detect abnormal conditions. Using wearable health sensors applied anomaly

detection techniques to monitor patients with chronic diseases. The system analyzed real-time data from different sensors and alerted healthcare providers when abnormal patterns appeared. This helped in early treatment and reduced hospital readmissions [29].

4. Data Processing and Aggregation in WSNs

WSNs generate large amounts of data, which may be redundant, irrelevant, or noisy. Efficient data processing and aggregation are necessary to ensure accurate decisions, reduce communication overhead, and save energy. AI techniques are widely used to filter, combine, and analyze sensor data [10,12].

4.1 AI-Based Data Filtering

AI techniques such as Machine Learning and Deep Learning can filter redundant and noisy data, so only useful information is transmitted.

- **Anomaly Detection:** AI models can detect abnormal readings that differ from normal patterns. For example, in environmental monitoring, ML models can detect incorrect temperature or humidity values caused by sensor faults and remove them [30].
- **Noise Reduction:** AI algorithms such as Support Vector Machines (SVM) or Autoencoders can reduce noise by learning the difference between useful data and interference, improving data quality and reducing processing load [30].

4.2 Data Aggregation Techniques

AI improves data aggregation by combining data from many sensors before sending it to the base station, which reduces communication cost and energy use.

- **Fuzzy Logic-Based Aggregation:** Fuzzy logic can combine sensor readings while considering uncertainty. For example, in smart agriculture, fuzzy logic can merge temperature, humidity, and soil moisture data to give a reliable view of field conditions [31].
- **Cluster-Based Aggregation:** AI methods such as K-means clustering can group nearby sensors or sensors with similar data. A cluster head collects and summarizes data from the group and sends only the summary, saving energy. These methods are effective in large WSNs.

4.3 Smart Data Fusion

Data fusion combines data from different sources in an intelligent way to produce more accurate and meaningful information.

- **Multi-Sensor Data Fusion:** AI models can combine data from different types of sensors to provide a better understanding of the environment. For example, in healthcare, data from heart rate, motion, and oxygen sensors can be fused using Neural Networks to give a complete view of a patient's condition [35].
- **Deep Learning for Data Fusion:** Deep Learning models such as CNNs and RNNs can learn complex relationships between different data sources. For example, in security systems, CNNs can combine camera data with motion sensor data to improve intrusion detection.

4.4 Improving Accuracy Through AI-Driven Aggregation

AI can improve the accuracy of aggregated data and make WSN outputs more reliable.

- **Regression Models for Prediction:** AI-based regression models can predict future trends based on past data. This allows the network to focus on important changes and reduce redundant data. For example, in energy monitoring, AI can predict high energy usage periods and adjust aggregation accordingly.
- **Collaborative Filtering:** In this approach, nearby nodes share and compare data. AI algorithms combine the most accurate readings and remove unreliable ones. This method improves data accuracy in

applications such as environmental monitoring, where temperature or pollution readings are combined from multiple nearby sensors [16].

N	Data Processing and Aggregation in WSNs	AI algorithms
1	filter redundant and noisy data	ML, DL and SVM
2	reduces communication cost and energy use	Fuzzy logic, K-means clustering
3	produce more accurate and meaningful information.	CNNs and RNNs

Table 2: Data Processing and Aggregation in WSNs

5. Challenges of Integrating AI into WSNs

Although Artificial Intelligence (AI) has great potential to enhance the performance and intelligence of Wireless Sensor Networks (WSNs), its integration is associated with several technical and practical challenges. These challenges stem from the inherent limitations of WSNs, including restricted energy resources, limited computational capabilities, and constrained communication infrastructures, in addition to the complexity of AI models themselves. The main challenges are discussed below [33].

5.1 Resource Constraints in WSNs

WSNs are typically composed of sensor nodes with limited processing power, memory, and battery capacity, which significantly restricts the deployment of advanced AI techniques.

Energy Consumption: Many AI algorithms, especially deep learning and reinforcement learning models, require substantial computational effort and energy. Since sensor nodes are usually battery-powered, executing such energy-intensive models can drastically reduce network lifetime. Therefore, developing energy-efficient AI solutions suitable for WSN environments remains a major research challenge [1, 34,33].

Limited Processing Power: Sensor nodes are generally equipped with low-performance processors, making it difficult to execute complex AI models locally. Algorithms such as neural networks often exceed the computational capabilities of these nodes. While offloading computations to edge devices or cloud servers can mitigate this issue, it introduces additional communication overhead and latency[33].

Memory Limitations: The storage capacity of sensor nodes is often insufficient for hosting large datasets or sophisticated AI models. Although techniques such as model compression and lightweight learning algorithms have been proposed, a tradeoff still exists between model complexity, accuracy, and memory usage.

5.2 Data Quality and Availability

The effectiveness of AI models in WSNs largely depends on the quality and availability of the collected data.

Noisy and Incomplete Data: Sensor readings are frequently affected by noise, environmental disturbances, hardware failures, or transmission errors, resulting in incomplete or unreliable data. Since AI models typically rely on high-quality data for training and inference, such imperfections can significantly degrade their performance. Designing AI techniques that are robust to noisy and sparse data is therefore essential [36].

Data Privacy and Security: In sensitive applications such as healthcare, military, and smart city systems, protecting the confidentiality and integrity of sensor data is critical. The use of AI often requires access to large volumes of data, increasing the risk of privacy breaches. Privacy-preserving techniques, including federated learning and differential privacy, are necessary to ensure secure and ethical AI deployment in WSNs.

6. Conclusion

This survey shows that building an efficient Wireless Sensor Network (WSN) requires choosing the best deployment scenario and focusing on several important factors. The most important factor is extending the network lifetime by allowing sensor nodes to work for as long as possible. This is especially important because WSNs are often deployed in remote and hard-to-reach areas.

To achieve this, clear design criteria must be defined, and system weaknesses should be reduced by using suitable artificial intelligence techniques. These AI algorithms can improve network performance, especially in routing and data aggregation, while saving energy.

WSNs are used in many daily-life applications, and each application has its own requirements. For example, in agriculture, data security may not be a main concern, but data accuracy and energy efficiency are very important. In such cases, AI-based algorithms are used to reduce energy consumption during data transmission while keeping the data reliable and accurate.

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