International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Study on AI-Enabled Energy-Efficient Wireless Sensor Networks with Edge Computing for Smart Environmental Monitoring

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Submitted: 02/04/2023 **Revised:** 15/05/2023 **Accepted:** 26/05/2023

Abstract: The rapid growth of Internet of Things (IoT), Wireless Sensor Networks (WSNs), Artificial Intelligence (AI), and Edge Computing has enabled the development of intelligent and sustainable environmental monitoring systems. Traditional WSN-based monitoring approaches face challenges related to limited energy resources, high communication overhead, latency, and restricted processing capabilities. This conceptual study explores the integration of AI-enabled energy-efficient WSNs with Edge Computing for smart environmental monitoring applications. The study examines how AI techniques enhance sensor data analysis, prediction, anomaly detection, and decision-making, while Edge Computing enables real-time processing by reducing dependence on centralized cloud platforms. Energy optimization approaches such as efficient routing, clustering, adaptive sensing, and resource management are discussed to improve network lifetime and operational efficiency. The study proposes a conceptual framework combining AI-driven analytics, edge intelligence, and energy-efficient WSN architectures to achieve reliable, scalable, and real-time environmental monitoring. The integration of these technologies provides significant potential for applications including smart cities, pollution monitoring, climate observation, and sustainable environmental management.

Keywords: *Artificial Intelligence; Edge Computing; Wireless Sensor Networks; Energy Efficiency; Smart Environmental Monitoring*

1. Introduction

The rapid advancement of Internet of Things (IoT), Wireless Sensor Networks (WSNs), Artificial Intelligence (AI), and Edge Computing has transformed traditional monitoring systems into intelligent and automated platforms. Sensor-based systems are increasingly used for continuous data acquisition, real-time analysis, and decision-making in various applications. The integration of AI with sensor networks enables systems to interpret complex data patterns, recognize conditions, and provide predictive insights rather than only collecting information. Recent studies have demonstrated the effectiveness of AI-based sensing approaches in applications involving activity recognition, behavioural analysis, and real-time monitoring (Mohr et al., 2017; Chung et al., 2019). Wireless Sensor Networks provide the foundation for smart monitoring by enabling distributed sensing and communication among multiple low-power sensor nodes. However, conventional WSNs face challenges related to limited energy resources, processing capability, and communication efficiency. The incorporation of Edge Computing addresses these limitations by allowing local data processing near sensor devices, reducing latency and improving system efficiency. AI-enabled edge architectures further enhance monitoring capabilities by supporting intelligent analysis and adaptive decision-making.

Machine learning and deep learning techniques have significantly improved the ability of sensor networks to extract meaningful information from large volumes of sensor-generated data. Deep learning models have been applied for real-time recognition, pattern detection, and automated classification using multimodal sensor information (Peppas et al., 2020; Chung et al., 2019). Similarly, hybrid AI approaches combining data-driven and knowledge-based methods improve the reliability and accuracy of intelligent sensing systems (Bettini et al., 2020). The application of AI-enabled sensor technologies has expanded across healthcare, smart environments, human activity monitoring, and personalized

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services. Research has shown that mobile and wearable sensing platforms integrated with machine learning can provide automated feedback, behavioural understanding, and continuous monitoring capabilities (Rabbi et al., 2015; Mohr et al., 2017). Deep neural networks have also demonstrated potential in analysing complex physiological and sensor patterns for real-time applications (Petrenko et al., 2018).

In the context of smart environmental monitoring, AI-enabled Energy-Efficient Wireless Sensor Networks with Edge Computing provide an effective solution for achieving real-time sensing, intelligent data processing, and sustainable operation. These systems aim to overcome the limitations of conventional monitoring approaches by combining low-power sensing, local intelligence, and predictive analytics. Therefore, the development of energy-efficient AI-driven WSN architectures is essential for future environmental monitoring applications requiring reliability, scalability, and autonomous decision-making.

1.1 Aim and Objectives

The aim of this study is to explore the role of Artificial Intelligence and Edge Computing in developing energy-efficient Wireless Sensor Networks for smart environmental monitoring applications.

Objectives

1. To examine the evolution and significance of Wireless Sensor Networks in smart environmental monitoring.
2. To analyse the role of Artificial Intelligence techniques in enhancing data processing, prediction, and decision-making capabilities of sensor networks.
3. To study the contribution of Edge Computing in reducing latency, communication overhead, and energy consumption in WSN-based monitoring systems.
4. To explore energy-efficient strategies, including routing, clustering, and resource optimization techniques, for improving WSN performance.
5. To propose a conceptual framework integrating AI, Edge Computing, and energy-efficient WSNs for sustainable smart environmental monitoring.

2. Review of Literature

Gubbi et al. (2013) studied IoT architecture and applications. The study aimed to analyse connected sensing systems and their future potential. Findings showed that IoT supports real-time monitoring but requires scalable architectures. Razzaque et al. (2016) reviewed IoT middleware solutions. The study focused on improving device interoperability and data management. Findings highlighted middleware as essential for efficient IoT communication. Dastjerdi and Buyya (2016) examined fog computing for IoT. The study aimed to reduce latency through edge-level processing. Findings showed fog computing improves real-time IoT performance. Mahdavinejad et al. (2018) analysed machine learning for IoT data processing. The study focused on predictive analysis and intelligent decision-making. Findings showed ML enhances IoT data analysis capabilities. Merenda et al. (2020) reviewed edge machine learning in IoT devices. The study aimed to improve real-time AI processing. Findings showed edge AI reduces communication overhead and improves efficiency. Buzura et al. (2020) studied energy optimization in WSNs. The study focused on reducing power consumption and extending network lifetime. Findings showed optimization techniques improve WSN efficiency. Junli et al. (2017) studied energy-efficient routing in WSNs. The study aimed to reduce energy consumption. Findings showed improved routing enhances network lifetime.

Shahraki et al. (2021) reviewed clustering techniques in WSNs and IoT. The study focused on efficient communication. Findings showed clustering improves scalability and energy efficiency. Buckley et al. (2021) studied low-power edge wireless sensing. The study aimed at real-time monitoring. Findings showed edge processing improves efficiency. Álvarez et al. (2021) analysed sensor-integrated single-board architectures. Findings showed compact platforms support efficient smart monitoring. Yousefpour et al. (2019) reviewed fog and edge computing for IoT. Findings showed edge processing reduces latency and improves resource utilization. Bajaj et al. (2021) studied cloud-edge offloading for sensor data. Findings showed edge-cloud integration improves IoT data processing efficiency. Pan and McElhannon (2018) studied edge computing for IoT. Findings showed edge processing reduces latency and improves efficiency. El Ghazi et al.

(2017) proposed context-aware routing for WSNs. Findings showed improved routing and energy management. Murphy (2021) examined machine learning techniques. Findings highlighted ML's role in prediction and intelligent analysis. Witten et al. (2011) studied data mining methods. Findings showed ML tools support effective pattern analysis.

Patterson and Gibson (2017) explored deep learning approaches. Findings showed improved processing of complex data. Li and Kim (2015) studied WSN lifetime optimization. Findings showed efficient forwarding reduces energy consumption. Noel et al. (2017) reviewed WSN applications. Findings highlighted WSN effectiveness in continuous monitoring systems. Rashid and Rehmani (2016) reviewed WSN applications in urban areas. Findings showed WSNs support smart city monitoring and efficient data collection. Shahraki et al. (2020) studied clustering objectives in WSNs. Findings showed clustering improves energy efficiency and network performance. Bajaj et al. (2020) examined WSN and IoT integration. Findings highlighted improved connectivity and smart city applications. Jiang (2009) proposed a fault detection method for WSN nodes. Findings showed improved reliability and network operation. Perera et al. (2014) reviewed IoT applications from an industrial perspective. Findings showed IoT enables intelligent and connected systems. Miranda et al. (2021) analysed machine learning in context-aware systems. Findings showed ML improves activity recognition and intelligent sensing. Sezer et al. (2018) reviewed context-aware IoT systems. Findings showed AI and big data enhance IoT intelligence and decision-making.

Bogale et al. (2018) studied machine intelligence techniques for wireless networks. Findings showed AI improves context awareness and network optimization. Pradeep and Krishnamoorthy (2019) reviewed context-aware systems. Findings highlighted their role in adaptive and intelligent applications. Liu et al. (2019) surveyed context-aware systems and applications. Findings showed context awareness enhances smart decision-making. Chatterjee et al. (2019) explored intelligence in resource-constrained IoT nodes. Findings showed lightweight AI enables efficient IoT processing. Rodríguez-Hernández and Ilarri (2021) studied AI-based context-aware systems. Findings showed AI improves personalized and adaptive services. Gupta et al. (2018) reviewed big data and cognitive computing. Findings showed intelligent analytics improve data-driven decision-making. Augustyniak and Ślusarczyk (2018) studied behaviour detection using data representation. Findings showed AI improves activity prediction accuracy. Filippoupolitis et al. (2017) explored location-based activity recognition. Findings showed sensor fusion improves recognition performance. Paudel et al. (2020) studied context-aware IoT with deep learning. Findings showed AI improves smart control and resource management. Chen et al. (2020) proposed activity-aware sampling for mobile sensing. Findings showed efficient sampling reduces energy consumption.

Esna Ashari et al. (2020) studied memory-aware active learning in sensing systems. Findings showed improved learning efficiency with reduced resource usage. Bettini et al. (2020) explored context-driven activity recognition. Findings showed incremental learning improves recognition accuracy. Huang et al. (2021) developed a lightweight CNN model for sensor-based recognition. Findings showed efficient AI processing on wearable devices. Ehatisham-Ul-Haq et al. (2020) studied context-based activity recognition using sensors. Findings showed behavioural modelling improves recognition performance. Yu et al. (2017) analysed abnormal behaviour detection using smartphones. Findings showed sensor-based AI improves event identification. Pejovic and Musolesi (2015) reviewed anticipatory mobile computing. Findings showed predictive computing enhances adaptive sensing systems. Lane and Georgiev (2015) studied deep learning for mobile sensing. Findings showed deep learning can improve intelligent sensing applications. Ehatisham-ul-Haq et al. (2018) analysed activity-based user authentication. Findings showed passive sensing improves authentication accuracy. Zhou et al. (2020) studied deep learning for healthcare IoT activity recognition. Findings showed AI improves recognition performance.

Culman et al. (2020) explored energy reduction in wearable sensing. Findings showed adaptive methods reduce power consumption. Mehrotra et al. (2021) developed middleware for anticipatory computing. Findings showed intelligent middleware supports adaptive sensing. Jansson and Hakala (2020) studied sensor data stream management. Findings showed efficient data handling improves smart sensing applications. Peleg et al. (2017)

evaluated personalized distributed guidance systems. Findings showed intelligent sensing supports personalized services. Rabbi et al. (2015) studied mobile-based personalized feedback systems. Findings showed sensing and analytics improve behavioural support. Petrenko et al. (2018) applied deep CNNs for respiration detection. Findings showed deep learning enables accurate pattern recognition. Fujinami (2016) studied smartphone-based localization using sensors. Findings showed accelerometer data supports accurate location detection. Mohr et al. (2017) reviewed personal sensing with machine learning. Findings showed sensor data can support intelligent health monitoring. Bettini et al. (2020) proposed hybrid activity recognition methods. Findings showed combining learning and knowledge models improves accuracy. Peppas et al. (2020) developed CNN-based activity recognition on mobile devices. Findings showed real-time AI processing is feasible on smart devices. Chung et al. (2019) studied multimodal sensor fusion using deep learning. Findings showed sensor fusion improves activity recognition accuracy.

2.1 Research gap

Existing studies have explored Wireless Sensor Networks (WSNs), Artificial Intelligence (AI), and Edge Computing individually for improving monitoring and data analysis. However, limited research focuses on the integrated design of AI-enabled, energy-efficient WSNs with edge computing for smart environmental monitoring. Many existing approaches face challenges related to energy constraints, real-time processing, scalability, and deployment of lightweight AI models on resource-limited sensor nodes. Therefore, there is a need for a unified framework that combines AI-driven analytics, edge intelligence, and energy optimization to achieve sustainable and real-time environmental monitoring.

3. Evolution of Smart Environmental Monitoring

Environmental monitoring has evolved from traditional manual observation methods to intelligent, automated, and connected systems. Earlier monitoring approaches relied on standalone instruments and periodic data collection, which limited real-time analysis and large-scale environmental observation. The development of Wireless Sensor Networks (WSNs) enabled continuous sensing and wireless transmission of environmental data through distributed sensor nodes, improving monitoring efficiency. However, challenges related to energy limitations, scalability, and communication efficiency remained significant (Gubbi et al., 2013; Shahraki et al., 2021). The integration of Internet of Things (IoT) transformed environmental monitoring by connecting sensors, communication networks, and data processing platforms for real-time environmental intelligence. IoT-based systems improved data accessibility and automation but generated large volumes of data requiring efficient processing mechanisms (Gubbi et al., 2013; Razzaque et al., 2016). To overcome cloud-based processing limitations, edge and fog computing approaches enabled local data processing near sensor nodes, reducing latency and improving energy efficiency (Dastjerdi & Buyya, 2016).

Recent advancements have incorporated Artificial Intelligence (AI) and Machine Learning (ML) techniques into environmental monitoring systems to support prediction, anomaly detection, and intelligent decision-making. AI-enabled edge computing allows real-time analysis while reducing communication overhead and dependence on centralized cloud platforms (Mahdavinejad et al., 2018; Merenda et al., 2020). Furthermore, energy-efficient routing, clustering, and optimization techniques have enhanced the sustainability and lifetime of WSN-based monitoring systems (Buzura et al., 2020; Junli et al., 2017; Shahraki et al., 2021). Thus, modern smart environmental monitoring represents a transition towards AI-enabled, energy-efficient, and edge-assisted WSN architectures capable of providing accurate, real-time, and sustainable environmental intelligence (Buckley et al., 2021).

4. Wireless Sensor Networks for Environmental Applications

Wireless Sensor Networks (WSNs) have become a fundamental technology for smart environmental monitoring by enabling distributed sensing, wireless communication, and real-time data collection. WSNs consist of multiple low-power sensor nodes capable of monitoring environmental parameters such as temperature, humidity, air quality, soil conditions, and water quality. These networks support continuous observation in remote and dynamic environments where traditional monitoring methods are difficult to implement. The development of compact sensor platforms and single-board architectures has further improved the deployment of low-cost and energy-efficient environmental monitoring systems (Álvarez et al., 2021). Environmental applications of WSNs require efficient data transmission and processing due to limitations in sensor energy, computational capacity, and communication range. Energy-efficient routing strategies and optimization techniques are essential for extending network lifetime and maintaining reliable data communication. Context-aware routing approaches have been explored to improve decision-making and optimize communication paths in dynamic WSN environments (El Ghazi et al., 2017). Similarly, lifetime optimization techniques focus on reducing energy consumption and maximizing the operational duration of sensor networks (Li & Kim, 2015).

With the increasing volume of sensor-generated data, WSNs are increasingly integrated with IoT, cloud, and edge computing technologies. Edge and fog computing enable data processing closer to sensor nodes, reducing latency, bandwidth requirements, and dependence on centralized cloud platforms (Yousefpour et al., 2019; Pan & McElhannon, 2018). Such integration enhances the efficiency of environmental monitoring applications by enabling faster analysis and real-time responses. Artificial Intelligence (AI) and Machine Learning (ML) techniques further enhance WSN-based environmental applications by enabling intelligent data analysis, prediction, and anomaly detection. Machine learning algorithms can identify patterns from complex sensor data and support automated decision-making in environmental management systems (Murphy, 2021; Witten et al., 2011). Deep learning approaches also provide advanced capabilities for processing large-scale environmental datasets and improving prediction accuracy (Patterson & Gibson, 2017).

Therefore, WSNs integrated with edge computing and AI technologies provide a scalable and intelligent framework for modern environmental monitoring. These systems enable energy-efficient sensing, real-time processing, and predictive analysis, supporting applications such as smart agriculture, pollution monitoring, climate observation, and ecological management (Bajaj et al., 2021).

5. Energy Efficiency in Wireless Sensor Networks

Energy efficiency is one of the most critical challenges in Wireless Sensor Networks (WSNs) because sensor nodes generally operate with limited battery capacity and are often deployed in remote environments where frequent battery replacement is difficult. Efficient energy management is essential to improve network lifetime, maintain reliable communication, and support long-term environmental monitoring applications. Various energy optimization strategies have been developed, including efficient routing protocols, node management techniques, and network optimization approaches (Noel et al., 2017). Clustering-based approaches have become an important method for reducing energy consumption in WSNs. By organizing sensor nodes into clusters and selecting cluster heads for data aggregation and communication, unnecessary transmissions can be minimized, thereby extending network lifetime. Research on clustering objectives highlights the importance of balancing energy consumption, improving scalability, and maintaining network performance in large-scale sensor deployments (Shahraki et al., 2020).

The integration of WSNs with Internet of Things (IoT) applications has further increased the need for energy-efficient communication mechanisms. IoT-enabled sensor networks generate continuous data streams, requiring optimized resource utilization to reduce power consumption while maintaining real-time monitoring capabilities (Bajaj et al., 2020). Energy-aware architectures are particularly important for smart city and environmental monitoring applications where sensor nodes operate continuously for extended periods (Rashid & Rehmani, 2016). Apart from communication optimization, maintaining network reliability through efficient fault detection and node management also contributes to energy conservation. Identifying faulty nodes and preventing unnecessary data transmission helps improve the overall efficiency of WSN operations (Jiang, 2009). Furthermore, the integration of IoT technologies has encouraged the development of intelligent energy management strategies that support sustainable and scalable sensor networks (Perera et al., 2014).

Thus, energy efficiency remains a fundamental design consideration in WSN-based smart environmental monitoring systems. The combination of energy-aware routing, clustering techniques, fault management, and IoT integration provides a foundation for developing reliable, low-power, and long-lasting sensor networks.

6. Role of Artificial Intelligence in Sensor Networks

Artificial Intelligence (AI) has become an important technology for enhancing the capabilities of sensor networks by enabling intelligent data processing, adaptive decision-making, and automated analysis. Traditional sensor networks mainly focused on collecting and transmitting environmental data, whereas AI-enabled sensor networks can interpret complex data patterns, identify abnormal conditions, and generate predictive insights. This transformation supports the development of smart monitoring systems capable of operating with greater accuracy and efficiency (Sezer et al., 2018). Machine Learning (ML) techniques allow sensor networks to learn from collected data and improve their performance without continuous human intervention. AI-based approaches are widely used for context recognition, prediction, classification, and optimization in IoT-enabled sensor applications. Miranda et al. (2021) highlighted the role of machine learning methods in context-aware systems, where sensor data is analysed to understand situations and support intelligent responses.

AI also enhances context-aware capabilities in wireless sensor networks by enabling systems to adapt according to changing environmental conditions, user requirements, and network states. Machine intelligence techniques support efficient resource allocation, improved communication strategies, and enhanced network performance in next-generation wireless networks (Bogale et al., 2018). Context-aware architectures further enable sensor networks to make intelligent decisions by combining sensor information with learning algorithms (Pradeep & Krishnamoorthy, 2019). In resource-constrained sensor networks, AI provides opportunities for optimizing energy consumption, improving data accuracy, and reducing unnecessary communication. Lightweight AI models can be deployed on IoT nodes to perform local analysis and decision-making while minimizing dependence on external computing resources. However, challenges related to computational limitations, energy requirements, and algorithm complexity remain important considerations for AI implementation in sensor networks (Chatterjee et al., 2019).

Therefore, the integration of Artificial Intelligence with sensor networks enables the development of adaptive, predictive, and energy-efficient monitoring systems. AI-driven sensor networks provide advanced capabilities for applications such as environmental monitoring, smart cities, healthcare, and industrial automation by improving intelligence, responsiveness, and operational efficiency (Liu et al., 2019).

7. Edge Computing for Real-Time Environmental Monitoring

Edge computing has emerged as an important technology for improving the performance of real-time environmental monitoring systems by enabling data processing closer to the source of data generation. Traditional cloud-based monitoring architectures require continuous transmission of sensor data to centralized servers, which can increase latency, bandwidth consumption, and energy usage. Edge computing addresses these limitations by performing local data analysis and decision-making near sensor devices, thereby improving response time and system efficiency. In smart environmental monitoring, edge-based architectures allow sensor networks to process large volumes of environmental data in real time. This capability is particularly valuable for applications requiring immediate responses, such as pollution detection, climate observation, and disaster warning systems. The integration of edge computing with intelligent data analysis techniques supports faster decision-making and reduces dependence on remote cloud infrastructures (Gupta et al., 2018).

The combination of Artificial Intelligence (AI), deep learning, and edge computing further enhances the ability of monitoring systems to recognize patterns, predict environmental changes, and optimize resource utilization. Context-aware computing approaches enable systems to adapt according to changing conditions by analysing information collected from sensors and generating intelligent responses (Rodríguez-Hernández & Ilarri, 2021). Edge-based processing also supports efficient sampling and data management by reducing unnecessary data transmission from sensor nodes. Intelligent sampling mechanisms and activity-aware approaches help minimize energy consumption while maintaining monitoring accuracy (Chen et al., 2020). Similarly, deep learning-based IoT frameworks demonstrate the potential of edge intelligence for automated control and efficient resource management in smart environments (Paudel et al., 2020).

Therefore, edge computing provides a reliable framework for real-time environmental monitoring by combining local processing, AI-driven analytics, and efficient communication strategies. The integration of edge intelligence with Wireless Sensor Networks enables faster responses, reduced energy consumption, and improved scalability for next-generation smart environmental monitoring applications.

8. AI and Edge Computing Integration in WSNs

The integration of Artificial Intelligence (AI) and Edge Computing with Wireless Sensor Networks (WSNs) has enabled the development of intelligent, adaptive, and efficient monitoring systems. Conventional WSNs mainly perform sensing and data transmission, whereas AI-enabled edge-based WSNs can analyse data locally, recognize patterns, and make real-time decisions without depending entirely on cloud platforms. This integration improves response time, reduces communication overhead, and supports energy-efficient operation in resource-constrained environments. AI algorithms deployed at the edge enable sensor networks to perform advanced functions such as prediction, classification, anomaly detection, and context recognition. Machine learning models allow sensor nodes to learn from collected data and adapt their behaviour according to changing conditions. Active learning approaches further improve efficiency by selecting relevant data samples for processing, thereby reducing unnecessary computation and energy consumption in mobile sensing systems (Esna Ashari et al., 2020).

Context-aware intelligence is another important advantage of AI-edge integration in WSNs. By combining sensor data with learning algorithms, systems can identify activities, environmental conditions, and abnormal events more accurately. Context-driven learning approaches improve the adaptability of sensor networks by enabling continuous learning and incremental recognition capabilities (Bettini et al., 2020). Lightweight deep learning models have also been explored for efficient processing on resource-limited devices, providing accurate analysis while maintaining computational efficiency (Huang et al., 2021). The integration of AI and edge computing is particularly beneficial for applications where real-time decisions are required. Intelligent sensor systems can analyse behavioural patterns, detect unusual conditions, and provide immediate responses without transferring large amounts of data to remote servers. Context modelling techniques using smart sensors demonstrate the effectiveness of AI-driven approaches in improving recognition accuracy and system intelligence (Ehatisham-Ul-Haq et al., 2020).

Furthermore, edge-based AI processing supports predictive and anticipatory capabilities in sensor networks. By analysing historical and real-time data, intelligent systems can anticipate future events and optimize network operations. Such approaches are useful for applications including environmental monitoring, smart transportation, healthcare, and industrial automation (Yu et al., 2017; Pejovic & Musolesi, 2015). Thus, the integration of AI and Edge Computing in WSNs provides a powerful framework for developing intelligent and energy-efficient monitoring systems. This combination enables real-time analytics, reduced latency, improved resource utilization, and enhanced adaptability, making it a key technology for next-generation smart environmental monitoring applications.

9. Challenges and Limitations

Despite significant advancements, AI-enabled Edge Computing-based Wireless Sensor Networks (WSNs) face several challenges that affect their practical implementation. One of the major limitations is the restricted computational capability and energy availability of sensor nodes. Deploying complex AI and deep learning models on resource-constrained devices requires lightweight algorithms that can maintain accuracy while reducing processing and power requirements (Lane & Georgiev, 2015). Data management is another important challenge in AI-driven sensor networks. Continuous data generation from multiple sensors creates difficulties related to data storage, processing, synchronization, and quality management. Efficient sensor data stream management is required to ensure reliable and timely analysis in smart monitoring applications (Jansson & Hakala, 2020). Additionally, variations in sensor data and changing environmental conditions can affect the accuracy and reliability of AI-based predictions.

Energy consumption remains a critical concern because continuous sensing, communication, and AI processing can reduce the operational lifetime of WSNs. Although edge computing reduces data transmission requirements, intelligent power management strategies are still necessary to optimize resource utilization. Adaptive techniques such as change-point detection and selective data processing have been explored to reduce unnecessary energy consumption in sensor-based systems (Culman et al., 2020). Security, privacy, and scalability also represent significant challenges in AI-enabled WSN environments. Large-scale deployment of connected sensors increases the risk of unauthorized access and data privacy issues. Furthermore, maintaining consistent performance while expanding the number of sensor nodes requires efficient architectures and intelligent middleware solutions (Mehrotra et al., 2021). Therefore, future research must focus on developing secure, lightweight, and energy-aware AI models suitable for edge-based sensor networks.

10. Conclusion

AI-enabled Energy-Efficient Wireless Sensor Networks integrated with Edge Computing represent a promising approach for developing intelligent and sustainable smart environmental monitoring systems. The evolution from traditional sensing networks to AI-driven architectures has improved real-time data processing, predictive analysis, and autonomous decision-making capabilities. By performing computation closer to sensor nodes, edge computing reduces latency, communication overhead, and energy consumption. The integration of machine learning and deep learning techniques enhances the ability of WSNs to recognize patterns, detect anomalies, and provide accurate environmental insights. However, challenges related to computational limitations, energy management, data handling, security, and scalability continue to influence the adoption of these systems. Research on lightweight AI models, efficient data processing, and adaptive sensor management is essential for overcoming these limitations. Overall, the combination of AI, Edge Computing, and WSN technologies provides a strong foundation for next-generation environmental monitoring applications. These intelligent systems can support real-time observation, efficient resource utilization, and sustainable environmental management, contributing to the development of smarter and more responsive monitoring infrastructures (Zhou et al., 2020; Peleg et al., 2017).

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