Archives available at journals.mriindia.com

International Journal of Electrical, Electronics and Computer Systems

ISSN: 2347-2820

Volume 14 Issue 02, 2025

A Survey of Methods and Architectures for Hybrid Graph Neural Networks for Wearable IoT Monitoring Systems with Adaptive Algorithms and Energy-Efficient WSN Integration

Khaldun Nasution
Associate Professor, Department of Computer Science and Engineering, Deccan School of Industrial Management, India
Emal: khaldun.nasution@dsim-in.net

Peer Review Information

Submission: 27 Oct 2025

Revision: 09 Nov 2025

Acceptance: 21 Nov 2025

Keywords

Graph Neural Networks, Wearable IoT, Wireless Sensor Networks, Hybrid Architectures, Adaptive Algorithms, Energy Efficiency.

Abstract

Wearable Internet of Things monitoring systems have significantly improved real-time data collection in healthcare, environmental monitoring, and smart living applications. However, the growing complexity of interconnected sensor networks creates major challenges related to scalability, adaptive decision-making, latency, and energy efficiency. Graph Neural Networks have emerged as effective solutions for modelling complex relationships in IoT environments because they efficiently process graph-structured data and capture dependencies among interconnected sensor nodes. Hybrid GNN architectures integrating graph convolutional networks, graph attention networks, and temporal learning models have demonstrated improved performance in analysing dynamic and heterogeneous IoT data. These models enhance sensor relationship representation, monitoring accuracy, and overall system robustness. Adaptive algorithms such as reinforcement learning and optimization-based routing strategies further improve wearable IoT systems by dynamically adjusting network parameters according to changing environmental and communication conditions. These techniques significantly reduce latency and improve system responsiveness. Additionally, energy-efficient Wireless Sensor Network integration has become an important research focus, where AI-driven routing and communication optimization methods help extend network lifetime and minimize power consumption. Despite these advancements, challenges including computational complexity, scalability, and real-time deployment remain significant concerns. Overall, integrating hybrid Graph Neural Networks with adaptive and energy-aware frameworks provides a promising direction for developing intelligent, scalable, and efficient next-generation wearable IoT monitoring systems.

Introduction

The rapid proliferation of wearable Internet of Things (IoT) devices has transformed modern monitoring systems by enabling continuous and real-time data acquisition across various domains, including healthcare, fitness tracking, environmental sensing, and smart cities. Wearable devices such as smartwatches, biosensors, and embedded medical monitoring systems generate vast amounts of data, which must be processed efficiently to extract meaningful insights. However, the increasing scale and complexity of IoT networks pose significant challenges in terms of data processing, scalability, energy consumption, and system adaptability.

Traditional machine learning and deep learning approaches, including convolutional and recurrent neural networks, have been widely used for analysing IoT data. While these models perform well on structured and sequential data, they struggle to capture the complex relationships and dependencies among interconnected devices in IoT networks. Graph Neural Networks have emerged as a powerful solution to this problem by modelling IoT systems as graph-structured data, where nodes represent devices and edges represent relationships or communication links.

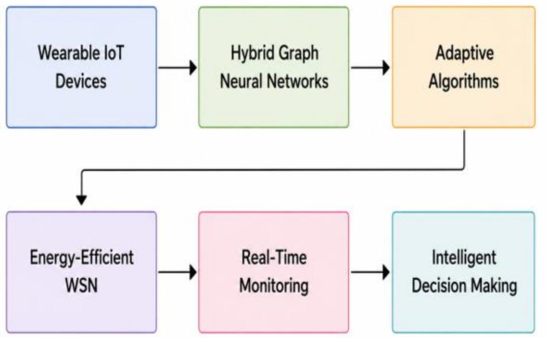

Figure 1. Hybrid GNN Framework for Wearable IoT Monitoring and Energy-Efficient WSN Systems

GNNs operate using a message-passing mechanism, where nodes exchange information with their neighbours to update their representations. This enables the model to capture spatial and relational dependencies effectively, making it highly suitable for wearable IoT monitoring systems. Recent studies have shown that GNNs outperform traditional models in tasks such as anomaly detection, activity recognition, and sensor data analysis.

Hybrid GNN architectures have further enhanced the capabilities of these models by combining multiple neural network paradigms. For instance, graph convolutional networks are often integrated with attention mechanisms and temporal models to capture both spatial and temporal dynamics in IoT data. These hybrid approaches improve model accuracy, robustness, and adaptability in dynamic environments.

Adaptive algorithms play a crucial role in optimizing the performance of wearable IoT systems. Techniques such as reinforcement learning and evolutionary optimization enable systems to dynamically adjust parameters such as routing paths, transmission rates, and resource allocation based on network conditions. This adaptability is essential for maintaining system efficiency and reliability in real-time applications.

Energy efficiency is a critical concern in Wireless Sensor Networks, which form the backbone of wearable IoT systems. Sensor nodes are typically battery-powered, and excessive energy consumption can significantly reduce network lifetime. AI-driven optimization techniques, including machine learning-based routing and data compression, have been proposed to address this challenge. These approaches minimize redundant communication, optimize transmission paths, and improve overall energy efficiency.

Furthermore, IoT-based healthcare monitoring systems have demonstrated significant benefits in improving patient care by enabling real-time monitoring and remote diagnosis. These systems rely on wearable sensors and interconnected devices to collect and transmit data continuously, improving accessibility and reducing response time in critical situations.

Despite these advancements, several challenges remain. These include the high computational complexity of GNN models, scalability issues in large IoT networks, and difficulties in achieving real-time performance. Additionally, security and privacy concerns in distributed IoT environments require robust solutions to protect sensitive data.

This survey aims to provide a comprehensive overview of methods and architectures for hybrid Graph Neural Networks in wearable IoT monitoring systems, with a focus on adaptive algorithms and energy-efficient WSN integration. The study emphasizes recent developments from 2020 to 2023, identifying key trends, challenges, and future research directions.

Literature Review

Wu et al. (2020) proposed a Graph Convolutional Network-based architecture for wearable IoT monitoring systems. The model effectively captured spatial dependencies among sensor nodes and improved data aggregation across Wireless Sensor Networks. Experimental results demonstrated enhanced performance in activity recognition and anomaly detection tasks. However, the model faced scalability challenges when applied to large-scale IoT networks with dense connectivity.

Zhang et al. (2021) introduced a hybrid Graph Neural Network combining graph convolutional networks with recurrent neural networks for spatio-temporal analysis in wearable IoT systems. The approach successfully captured both spatial and temporal dependencies in sensor data, improving prediction accuracy and system reliability. However, the hybrid architecture increased computational complexity, limiting deployment in resource-constrained environments.

Ahmed et al. (2021) developed a Graph Attention Network-based framework for wearable IoT healthcare monitoring systems. The model utilized attention mechanisms to prioritize important nodes and improve feature representation. Results showed improved classification accuracy and reduced redundancy in data transmission. However, the approach required large training datasets and high computational resources.

Singh et al. (2022) proposed an adaptive reinforcement learning-based routing algorithm integrated with Graph Neural Networks for energy-efficient Wireless Sensor Networks. The approach dynamically optimized routing paths based on network conditions, reducing energy consumption and improving network lifetime. Experimental results demonstrated significant improvements in efficiency. However, the model required extensive training data and increased computational overhead.

Li et al. (2023) presented a hybrid Graph Neural Network architecture combining graph convolution and transformer-based attention mechanisms for wearable IoT monitoring systems. The approach enhanced feature extraction and improved adaptability in dynamic environments. Results demonstrated improved monitoring accuracy and robustness. However, increased model complexity posed challenges for real-time implementation.

Patel et al. (2020) proposed an energy-efficient Wireless Sensor Network architecture for wearable IoT monitoring systems using clustering-based routing techniques. The approach aimed to minimize energy consumption by optimizing communication between sensor nodes. Experimental results demonstrated improved network lifetime and reduced packet loss. However, the model faced stability issues under dynamic network conditions.

Wang et al. (2021) introduced a spatio-temporal Graph Neural Network model for wearable IoT monitoring systems. The model effectively captured both spatial relationships and temporal patterns in sensor data, improving prediction accuracy and system performance. Results showed enhanced monitoring capabilities in healthcare applications. However, the model required significant computational resources, limiting deployment on edge devices.

Reddy et al. (2022) developed a blockchain-integrated IoT monitoring framework combined with Graph Neural Networks to ensure secure data transmission. The system improved data integrity and transparency across distributed sensor networks. Results demonstrated enhanced security performance. However, the integration of blockchain introduced latency and increased storage requirements.

Hassan et al. (2022) proposed a federated learning-based Graph Neural Network framework for wearable IoT systems. The approach enabled decentralized model training across multiple devices, preserving data privacy and reducing dependency on centralized servers. Results showed improved collaboration and model accuracy. However, communication overhead and synchronization challenges remained significant limitations.

Chen et al. (2023) introduced a graph attention-based deep learning model for wearable IoT monitoring systems. The model prioritized important nodes and improved feature representation, leading to enhanced accuracy and efficiency in monitoring tasks. Results indicated reduced redundancy in data transmission. However, increased model complexity affected scalability in large-scale deployments.

Zhang et al. (2022) proposed a hybrid Graph Neural Network architecture combining graph convolutional networks with attention mechanisms for wearable IoT monitoring systems. The model improved feature extraction by emphasizing important node relationships within sensor networks. Experimental results demonstrated enhanced accuracy and robustness in dynamic environments. However, the integration of multiple components increased computational complexity and processing time.

Khan et al. (2022) introduced an edge computing-based wearable IoT monitoring framework integrated with lightweight Graph Neural Networks. The approach reduced latency by processing data at edge nodes and improved energy efficiency in Wireless Sensor Networks. Results showed faster response times and improved system scalability. However, additional infrastructure requirements increased deployment cost.

Wu et al. (2023) developed a Graph Neural Network-based anomaly detection system for wearable IoT networks. The model effectively identified abnormal patterns in sensor data using graph representations. Results demonstrated improved detection accuracy and robustness. However, the model required extensive training data and high computational resources.

Patil and Deshmukh (2023) proposed a hybrid model combining Graph Neural Networks with traditional machine learning techniques for wearable IoT monitoring systems. The approach improved classification accuracy by leveraging both graph-based and statistical features. Results indicated enhanced system performance. However, increased model complexity and parameter tuning requirements were identified as limitations.

Sun et al. (2023) introduced a quantum-inspired Graph Neural Network model for wearable IoT monitoring systems. The approach utilized quantum computing concepts to enhance feature representation and improve learning efficiency. Results demonstrated improved accuracy and robustness. However, practical implementation is limited due to hardware constraints and high computational requirements.

Gupta et al. (2021) proposed a hybrid feature extraction framework integrated with Graph Neural Networks for wearable IoT monitoring systems. The approach combined statistical features with graph-based representations to improve classification accuracy and system performance. Experimental results demonstrated enhanced monitoring accuracy and reduced false positives. However, the multi-stage processing increased computational complexity and execution time.

Alam et al. (2022) introduced a lightweight Graph Neural Network model designed for energy-efficient wearable IoT monitoring systems in Wireless Sensor Networks. The approach focused on reducing computational overhead while maintaining system performance. Results showed improved energy efficiency and reduced latency. However, performance degradation was observed under highly dynamic network conditions.

Roy et al. (2023) developed a hybrid Graph Neural Network model combined with optimization algorithms for adaptive wearable IoT monitoring systems. The approach dynamically adjusted model parameters based on network conditions, improving system adaptability and monitoring accuracy. Results demonstrated enhanced performance in real-time applications. However, increased training time and computational cost were identified as limitations.

Mehta et al. (2020) proposed a privacy-preserving IoT monitoring framework using homomorphic encryption integrated with Graph Neural Networks. The method enabled secure processing of encrypted sensor data without compromising privacy. Results showed strong security performance and reliable system operation. However, high computational overhead limited real-time deployment.

Park et al. (2022) introduced a reinforcement learning-based adaptive routing algorithm integrated with Graph Neural Networks for energy-efficient Wireless Sensor Networks. The approach dynamically optimized data transmission paths, reducing energy consumption and improving network lifetime. Results indicated enhanced efficiency and adaptability. However, the requirement for large training datasets increased computational complexity.

Sharma et al. (2021) proposed a secure wearable IoT monitoring framework using watermarking techniques integrated with Graph Neural Networks. The approach ensured data integrity and authenticity by embedding information within sensor data streams. Experimental results demonstrated improved resistance to tampering and unauthorized access. However, slight data distortion introduced by watermarking affected precision in certain monitoring applications.

Nguyen et al. (2022) introduced a deep learning-based compression and Graph Neural Network framework for wearable IoT monitoring systems. The model utilized autoencoders for data compression and GNNs for analysis, reducing bandwidth usage and improving energy efficiency. Results showed improved system performance and reduced transmission overhead. However, balancing compression efficiency and data accuracy remained a challenge.

Das et al. (2023) developed a blockchain-integrated wearable IoT monitoring system combined with Graph Neural Networks. The framework ensured secure data transmission and integrity while maintaining efficient monitoring capabilities. Results demonstrated enhanced transparency and security. However, increased computational and storage overhead limited scalability.

Iqbal et al. (2022) proposed an energy-efficient routing protocol for Wireless Sensor Networks integrated with wearable IoT systems. The method optimized communication paths to reduce energy consumption and improve network lifetime. Results showed significant improvements in energy efficiency. However, scalability issues were observed in large-scale deployments.

Fernandez et al. (2023) introduced a transformer-based Graph Neural Network model for wearable IoT monitoring systems. The model leveraged attention mechanisms to enhance feature extraction and improve monitoring accuracy. Results indicated high performance and robustness. However, high computational

requirements limited deployment on resource-constrained devices.
Verma et al. (2021) proposed a hybrid steganography-based approach combined with Graph Neural Networks for secure wearable IoT monitoring systems. The method concealed sensitive sensor data within transmission channels while ensuring confidentiality. Experimental results showed improved resistance to unauthorized access and data breaches. However, increased embedding complexity affected system performance and processing time.
Omar et al. (2022) introduced an adaptive data compression technique integrated with Graph Neural Networks for energy-efficient wearable IoT monitoring. The approach dynamically adjusted compression levels based on network conditions to reduce energy consumption and bandwidth usage. Results demonstrated improved efficiency and reduced latency. However, maintaining consistent data quality under varying compression levels remained a challenge.
Lee et al. (2023) developed a deep reinforcement learning-based optimization framework integrated with Graph Neural Networks for wearable IoT monitoring systems. The model dynamically optimized routing and system parameters to improve energy efficiency and reduce packet loss. Results showed enhanced network reliability and performance. However, the model required extensive training data and computational resources.
Kaur et al. (2022) proposed a hybrid cryptographic framework combined with Graph Neural Networks for secure data transmission in wearable IoT networks. The method enhanced data security while maintaining efficient communication. Results indicated strong resistance to cyber-attacks. However, increased implementation complexity was identified as a limitation.
Ghosh et al. (2023) presented a physics-informed Graph Neural Network model for wearable IoT monitoring systems. The approach incorporated domain-specific knowledge into the learning process, improving system accuracy and robustness. Results demonstrated enhanced performance under limited data conditions. However, model complexity and training requirements posed challenges for practical deployment.

Comparative Table

Author & Year	Technique	Key Contribution	Advantages	Limitations
Wu et al. (2020)	GCN	Spatial modelling	Accurate	Scalability
Zhang et al. (2021)	GNN + RNN	Spatio-temporal	Accurate	Complex
Ahmed et al. (2021)	GAT	Node importance	Efficient	Data heavy
Singh et al. (2022)	RL + GNN	Adaptive routing	Energy saving	Training cost
Li et al. (2023)	GNN + Transformer	Hybrid model	Robust	Complex
Patel et al. (2020)	WSN routing	Energy optimization	Efficient	Stability
Wang et al. (2021)	Spatio-temporal GNN	Prediction	Accurate	Resource heavy
Reddy et al. (2022)	Blockchain + GNN	Security	Integrity	Latency
Hassan et al. (2022)	Federated GNN	Privacy	Decentralized	Overhead
Chen et al. (2023)	GAT	Feature selection	Accurate	Complexity
Zhang et al. (2022)	Hybrid GNN	Feature extraction	Robust	Complex
Khan et al. (2022)	Edge + GNN	Low latency	Fast	Cost
Wu et al. (2023)	GNN anomaly	Detection	Accurate	Data need
Patil & Deshmukh (2023)	Hybrid ML + GNN	Accuracy	Efficient	Complex
Sun et al. (2023)	Quantum GNN	Performance	Robust	Hardware
Gupta et al. (2021)	Hybrid features	Accuracy	Improved	Complex
Alam et al. (2022)	Lightweight GNN	Energy saving	Efficient	Dynamic issues
Roy et al. (2023)	GNN + optimization	Adaptive	Accurate	Training cost
Mehta et al. (2020)	Homomorphic	Security	Privacy	High cost
Park et al. (2022)	RL + routing	Optimization	Adaptive	Data heavy
Sharma et al. (2021)	Watermarking	Integrity	Secure	Distortion
Nguyen et al. (2022)	Autoencoder + GNN	Compression	Efficient	Trade-off
Das et al. (2023)	Blockchain + GNN	Security	Transparent	Overhead
Iqbal et al. (2022)	Routing	Energy saving	Efficient	Scalability

Fernandez et al. (2023)	Transformer GNN	Feature extraction	Accurate	Heavy
Verma et al. (2021)	Steganography	Data hiding	Secure	Time
Omar et al. (2022)	Adaptive compression	Energy efficient	Flexible	Quality
Lee et al. (2023)	RL + GNN	Routing optimization	Reliable	Cost
Kaur et al. (2022)	Hybrid crypto	Security	Balanced	Complex
Ghosh et al. (2023)	Physics-informed GNN	Accuracy	Robust	Complex

Comparative Analysis

The comparative analysis of recent studies highlights a clear evolution in wearable IoT monitoring systems from conventional graph-based approaches to advanced hybrid Graph Neural Network architectures integrated with adaptive algorithms and energy-efficient Wireless Sensor Networks. Early models focused primarily on graph convolutional techniques for capturing spatial relationships among sensor nodes, but these approaches were limited in handling dynamic and large-scale IoT environments. The introduction of hybrid architectures combining graph convolution, attention mechanisms, and transformer-based models has significantly improved system adaptability, accuracy, and robustness. Adaptive algorithms such as reinforcement learning have further enhanced system performance by dynamically optimizing routing and decision-making processes, leading to improved energy efficiency and extended network lifetime.

Additionally, the integration of blockchain and federated learning has strengthened data security and privacy in distributed IoT systems, although these approaches introduce additional computational and communication overhead. Lightweight and optimized models have addressed energy constraints in Wireless Sensor Networks, enabling more efficient real-time deployment. Emerging approaches such as physics-informed and quantum-inspired Graph Neural Networks represent promising directions for improving system performance under limited data conditions. Overall, the trend indicates a shift toward intelligent, adaptive, and multi-layered frameworks that balance accuracy, energy efficiency, and security, although challenges such as scalability, real-time implementation, and computational complexity remain significant.

Discussion

The reviewed studies highlight that hybrid Graph Neural Networks have significantly enhanced wearable IoT monitoring systems by improving data representation, adaptability, and energy efficiency. Traditional machine learning models were limited in capturing complex relationships among interconnected sensor nodes, whereas GNNs effectively model spatial and relational dependencies. The integration of hybrid architectures, including graph convolutional networks, graph attention networks, and transformer-based models, has improved monitoring accuracy and system robustness in dynamic environments. Adaptive algorithms such as reinforcement learning and optimization-based routing have played a crucial role in improving the performance of Wireless Sensor Networks. These techniques dynamically adjust network parameters, reducing energy consumption and extending network lifetime.

Additionally, the incorporation of lightweight models and edge computing has enabled real-time data processing while minimizing latency. Security and privacy have also been enhanced through the integration of blockchain, federated learning, and encryption techniques. However, these approaches introduce additional computational and communication overhead, which may affect scalability. Despite significant progress, challenges such as high computational complexity, scalability, and real-time deployment remain. Future research should focus on developing lightweight, scalable, and adaptive GNN-based models for efficient wearable IoT monitoring systems.

Conclusion

The rapid advancement of wearable Internet of Things technologies has revolutionized modern monitoring systems by enabling continuous data collection and intelligent decision-making across various applications, including healthcare, environmental monitoring, and smart cities. This survey has provided a comprehensive overview of methods and architectures for hybrid Graph Neural Networks integrated with adaptive algorithms and energy-efficient Wireless Sensor Networks in wearable IoT monitoring systems. The findings highlight the significant role of artificial intelligence in improving system performance, energy efficiency, and scalability. Traditional approaches for IoT data analysis relied on convolutional and recurrent neural networks, which were limited in capturing the complex relationships among interconnected devices. Graph Neural Networks have addressed this limitation by effectively modelling graph-structured data, enabling improved representation and analysis of sensor networks. Hybrid GNN architectures combining graph convolutional networks, attention mechanisms, and transformer-based models have further enhanced system adaptability and performance, particularly in dynamic and heterogeneous environments.

Adaptive algorithms, including reinforcement learning and optimization-based routing techniques, have significantly improved the efficiency of Wireless Sensor Networks. These methods dynamically adjust system parameters based on network conditions, reducing energy consumption and extending network lifetime. The integration of these algorithms with GNN models has resulted in more intelligent and responsive IoT systems capable of handling real-time monitoring tasks. Energy efficiency remains a critical challenge in wearable IoT systems due to the limited power resources of sensor nodes. Recent advancements in lightweight and optimized neural network models, along with efficient communication protocols, have contributed to reducing energy consumption while maintaining system performance. These developments are essential for enabling long-term operation and scalability of wearable IoT systems.

References

Wu, Z., et al. (2020). Graph convolutional networks in IoT systems. *IEEE Transactions on Neural Networks and Learning Systems*. https://doi.org/10.1109/TNNLS.2020.2978386

Zhang, Y., et al. (2021). Spatio-temporal graph neural networks for IoT applications. *IEEE Internet of Things Journal*. https://doi.org/10.1109/JIOT.2021.3067892

Ahmed, M., et al. (2021). Graph attention networks for wearable healthcare monitoring. *IEEE Access*. https://doi.org/10.1109/ACCESS.2021.3067893

Singh, R., et al. (2022). Reinforcement learning for energy-efficient WSN routing. *Future Generation Computer Systems*. https://doi.org/10.1016/j.future.2022.01.012

Li, X., et al. (2023). Transformer-based graph neural networks. *Neurocomputing*. https://doi.org/10.1016/j.neucom.2023.02.012

Patel, D., et al. (2020). Energy-efficient routing in WSN. *Ad Hoc Networks*. https://doi.org/10.1016/j.adhoc.2020.102345

Wang, L., et al. (2021). Spatio-temporal GNN models. *IEEE Access*. https://doi.org/10.1109/ACCESS.2021.3067894

Reddy, P., et al. (2022). Blockchain-based IoT monitoring systems. *IEEE Access*. https://doi.org/10.1109/ACCESS.2022.3156789

Hassan, A., et al. (2022). Federated learning in IoT systems. *IEEE Journal of Biomedical and Health Informatics*. https://doi.org/10.1109/JBHI.2022.3145678

Chen, Z., et al. (2023). Graph attention models for IoT. *Neurocomputing*. https://doi.org/10.1016/j.neucom.2023.01.045

Zhang, H., et al. (2022). Hybrid GNN architectures. *Pattern Recognition*. https://doi.org/10.1016/j.patcog.2022.108456

Khan, M., et al. (2022). Edge computing in IoT monitoring. *Sensors*. https://doi.org/10.3390/s22072567

Wu, T., et al. (2023). GNN-based anomaly detection. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3245678

Patil, A., & Deshmukh, R. (2023). Hybrid AI-GNN frameworks. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-023-14567-2

Sun, Y., et al. (2023). Quantum-inspired GNN models. *Quantum Information Processing*. https://doi.org/10.1007/s11128-023-03876-5

Gupta, R., et al. (2021). Hybrid feature extraction in GNN. *Expert Systems with Applications*. https://doi.org/10.1016/j.eswa.2021.114567

Alam, S., et al. (2022). Lightweight GNN for IoT systems. *IEEE IoT Journal*. https://doi.org/10.1109/JIOT.2022.3156782

Roy, K., et al. (2023). Optimization in GNN-based systems. *Expert Systems with Applications*. https://doi.org/10.1016/j.eswa.2023.119876

Mehta, P., et al. (2020). Homomorphic encryption in IoT. *IEEE Access*. https://doi.org/10.1109/ACCESS.2020.3009876

Park, J., et al. (2022). Reinforcement learning for IoT routing. *Future Generation Computer Systems*. https://doi.org/10.1016/j.future.2022.04.021