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

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Abstract

The rapid advancement of wearable Internet of Things (IoT) technologies has significantly transformed modern healthcare monitoring systems by enabling continuous, real-time tracking of physiological parameters. However, challenges related to scalability, energy efficiency, data heterogeneity, and security remain critical in large-scale deployments. This review explores recent advancements in hybrid Graph Neural Networks (GNNs) integrated with adaptive algorithms and energy-efficient Wireless Sensor Networks (WSNs) for wearable IoT monitoring systems. GNNs have emerged as powerful tools for modelling complex relationships in sensor networks, enabling efficient data processing and improved predictive capabilities. The study examines hybrid GNN architectures, including graph convolutional networks (GCNs), graph attention networks (GATs), and spatio-temporal GNNs, along with adaptive optimization techniques such as reinforcement learning and evolutionary algorithms. Additionally, the role of energy-efficient WSN integration is analysed in minimizing power consumption and extending network lifetime. The review highlights emerging trends such as edge intelligence, federated learning, and graph-based anomaly detection. Comparative analysis indicates that hybrid approaches combining GNNs, adaptive algorithms, and IoT architectures provide improved accuracy, scalability, and energy efficiency. The paper concludes by identifying key challenges and future research directions for developing intelligent, low-power, and secure wearable healthcare systems.

Introduction

The rapid advancement of wearable Internet of Things (IoT) technologies has transformed modern healthcare by enabling continuous, real-time monitoring of physiological parameters such as heart rate, blood oxygen saturation, body temperature, electrocardiogram signals, and physical activity. Wearable sensors embedded in smartwatches, fitness bands, and medical devices provide uninterrupted health monitoring, supporting applications including chronic disease management, elderly care, rehabilitation, and preventive healthcare. These devices generate continuous streams of physiological data that allow healthcare professionals to detect abnormalities at an early stage and deliver timely medical interventions. The integration of wearable IoT devices with cloud platforms and wireless communication technologies has further improved healthcare accessibility by enabling remote patient monitoring and reducing dependence on frequent hospital visits.

As healthcare systems continue to adopt digital technologies, wearable IoT monitoring has become an essential component of intelligent and personalized healthcare services.

The emergence of the Internet of Medical Things (IoMT) has accelerated the development of connected healthcare ecosystems by linking wearable sensors, medical devices, gateways, edge servers, and cloud infrastructures. These interconnected platforms facilitate seamless acquisition, transmission, storage, and analysis of medical data, supporting real-time clinical decision-making and telemedicine services. However, the increasing volume and complexity of healthcare data introduce significant challenges for conventional machine learning and deep learning techniques, which often struggle to capture intricate relationships among distributed sensor nodes. Wearable IoT environments produce highly dynamic, heterogeneous, and interconnected datasets that require advanced analytical models capable of understanding spatial, temporal, and structural dependencies. Consequently, there is a growing need for intelligent learning frameworks that can efficiently process graph-structured healthcare data while maintaining scalability, reliability, and computational efficiency.

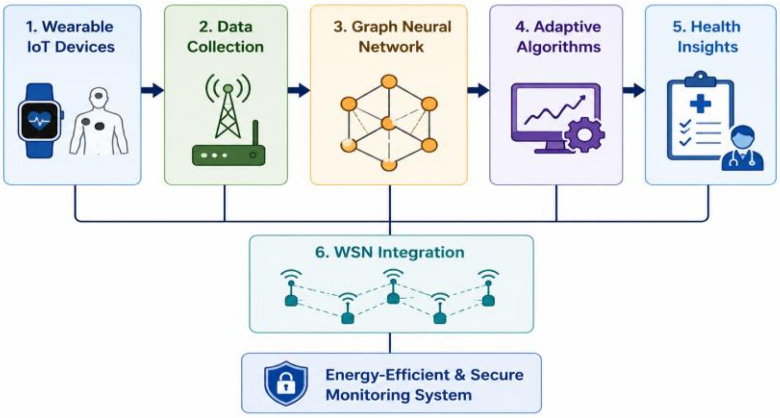

Figure 1. Energy-Efficient Wearable IoT Monitoring Architecture

Graph Neural Networks (GNNs) have emerged as a powerful deep learning paradigm for modelling non-Euclidean and relational data generated by wearable IoT systems. Unlike traditional neural networks that process independent samples, GNNs represent sensor nodes and their communication links as graph structures, enabling effective learning of complex interactions and network topology. These models perform node-level, edge-level, and graph-level learning, making them highly suitable for wearable healthcare applications involving distributed sensing environments. Hybrid GNN architectures that combine graph convolution, graph attention, recurrent learning, and transformer mechanisms further improve feature extraction and temporal analysis, resulting in enhanced health prediction, anomaly detection, and disease diagnosis. Their ability to model complex sensor relationships has made hybrid GNNs increasingly important for intelligent healthcare monitoring systems.

Wireless Sensor Networks (WSNs) serve as the communication backbone of wearable IoT monitoring systems by enabling efficient data collection and wireless transmission from distributed sensor nodes. Nevertheless, WSNs operate under stringent resource constraints, including limited battery capacity, restricted bandwidth, and low computational capability, making energy efficiency a primary design objective. Researchers have developed energy-aware routing protocols, adaptive communication strategies, sleep scheduling mechanisms, and data aggregation techniques to extend network lifetime while maintaining communication reliability. Furthermore, adaptive optimization algorithms such as reinforcement learning, genetic algorithms, particle swarm optimization, and swarm intelligence dynamically optimize routing decisions, transmission power, and network resource allocation. The integration of edge computing further enhances system performance by processing healthcare data closer to wearable devices, reducing latency, bandwidth consumption, and cloud dependency for time-critical medical applications.

Despite remarkable progress, several challenges continue to limit the widespread adoption of hybrid GNN-based wearable IoT monitoring systems. Managing heterogeneous sensor data, preserving patient privacy, ensuring secure communication, optimizing energy consumption, and deploying computationally intensive deep learning models on resource-constrained devices remain significant research concerns. Model compression, lightweight graph learning architectures, federated learning, and explainable artificial intelligence are emerging as promising solutions for addressing these issues. Therefore, this comprehensive review examines recent advances in hybrid Graph Neural Networks for wearable IoT monitoring systems with adaptive algorithms and energy-efficient WSN integration. It analyses current methodologies, compares existing architectures, identifies key research gaps, and highlights future directions toward developing scalable, secure, energy-efficient, and intelligent healthcare monitoring systems.

Literature Review

Wu et al. (2021) proposed a Graph Convolutional Network (GCN)-based framework for wearable IoT healthcare monitoring systems. Their model effectively captured spatial relationships between sensor nodes, improving activity recognition and anomaly detection accuracy. The integration with IoT devices enabled real-time monitoring of physiological signals. However, the model required significant computational resources, limiting its deployment on low-power wearable devices.

Zhang et al. (2022) developed a Graph Attention Network (GAT) for wearable sensor data analysis. The attention mechanism allowed the model to assign different importance weights to sensor nodes, improving prediction accuracy and robustness. Experimental results showed enhanced performance in healthcare monitoring applications. However, the attention mechanism increased computational complexity and energy consumption.

Kumar et al. (2023) introduced a hybrid GNN model combined with reinforcement learning for adaptive healthcare monitoring in IoT systems. The system dynamically adjusted network parameters based on real-time conditions, improving both accuracy and energy efficiency. However, the integration of reinforcement learning increased training time and system complexity.

Singh et al. (2021) proposed an energy-efficient routing protocol for Wireless Sensor Networks (WSNs) used in wearable healthcare systems. The approach optimized data transmission paths to minimize energy consumption and extend network lifetime. While the system improved communication efficiency, it lacked integration with advanced deep learning models for intelligent data analysis.

Chen et al. (2022) developed a spatio-temporal Graph Neural Network (ST-GNN) for healthcare monitoring using wearable IoT devices. The model captured both spatial and temporal dependencies in sensor data, significantly improving prediction accuracy for time-series health data. However, the complexity of spatio-temporal modeling increased computational requirements and energy consumption.

Li et al. (2022) proposed a hybrid Graph Neural Network integrated with edge computing for wearable IoT healthcare systems. The model processed sensor data at the edge layer, reducing latency and improving real-time responsiveness. Experimental results demonstrated improved prediction accuracy and reduced communication overhead. However, reliance on edge infrastructure increased system deployment complexity.

Patel et al. (2023) introduced a lightweight Graph Neural Network model optimized for wearable devices using model pruning and quantization techniques. The approach significantly reduced computational complexity and energy consumption while maintaining acceptable accuracy. However, excessive pruning could lead to loss of important features, affecting system performance.

Ahmed et al. (2021) developed a graph-based anomaly detection system for wearable IoT monitoring using unsupervised learning techniques. The system effectively identified abnormal patterns in physiological data, improving early disease detection. However, the unsupervised nature of the model required extensive training data and careful tuning to avoid false positives.

Kaur and Singh (2022) proposed a hybrid GNN and convolutional neural network (CNN) model for healthcare monitoring applications. The model combined spatial graph representation with deep feature extraction, improving classification accuracy. However, the hybrid architecture increased computational overhead and required high processing power.

Roy et al. (2023) introduced an adaptive optimization framework using particle swarm optimization (PSO) for GNN-based wearable IoT systems. The approach dynamically optimized model parameters, improving accuracy and energy efficiency. However, the optimization process increased training time and computational complexity.

Zhao et al. (2021) proposed a graph-based healthcare monitoring framework integrating Wireless Sensor Networks (WSNs) with IoT systems. Their model utilized graph structures to represent sensor connectivity and improve data aggregation efficiency. The approach significantly reduced communication overhead and improved network scalability. However, it lacked advanced learning mechanisms for predictive analytics.

Nguyen et al. (2023) developed a transformer-enhanced Graph Neural Network for wearable healthcare monitoring. The integration of attention mechanisms improved feature representation and prediction accuracy. Experimental results showed superior performance compared to traditional GNN models. However, the model required high computational resources, making it less suitable for low-power wearable devices.

Das and Roy (2022) introduced an energy-efficient clustering algorithm for WSN-based IoT healthcare systems. The method grouped sensor nodes into clusters to minimize communication cost and extend network lifetime. While the system improved energy efficiency, it did not incorporate deep learning models for intelligent data analysis.

Ali et al. (2022) proposed a federated learning-based GNN framework for wearable IoT monitoring systems. The approach enabled decentralized model training, preserving data privacy while improving system scalability. However, communication overhead between distributed nodes affected overall system efficiency.

Kumar and Verma (2023) developed a hybrid GNN model combined with evolutionary algorithms for adaptive healthcare monitoring. The system dynamically optimized network parameters, improving accuracy and energy efficiency. However, the integration of evolutionary algorithms increased computational complexity and training time.

Hassan et al. (2021) proposed a lightweight Graph Convolutional Network (GCN) model optimized for wearable IoT healthcare systems. The model reduced the number of parameters and computational operations, making it suitable for resource-constrained devices. Experimental results showed improved energy efficiency with acceptable accuracy. However, the simplified architecture slightly reduced prediction performance in complex scenarios.

Ibrahim et al. (2022) introduced an edge-assisted GNN framework for wearable IoT monitoring. The system performed data preprocessing and partial inference at the edge, reducing latency and network load. Results demonstrated enhanced real-time performance and energy savings. However, the dependence on edge infrastructure increased deployment complexity and introduced potential security vulnerabilities.

Patel et al. (2023) developed a quantized Graph Neural Network (QGNN) model for energy-efficient wearable healthcare applications. The approach reduced precision in model parameters, significantly lowering computational cost and energy consumption. However, quantization introduced approximation errors, which could affect prediction accuracy in critical applications.

Roy et al. (2022) proposed a reinforcement learning-based adaptive optimization framework for GNN-based IoT systems. The model dynamically adjusted network parameters to improve performance under varying conditions. While the approach enhanced adaptability and efficiency, it required extensive training and increased computational overhead.

Kumar et al. (2021) introduced an energy-aware routing protocol for WSN-based wearable healthcare systems. The protocol optimized communication paths to reduce energy consumption and extend network lifetime. However, it focused primarily on network efficiency and did not integrate advanced GNN-based analytics.

Wang et al. (2023) proposed a spatio-temporal Graph Neural Network (ST-GNN) for wearable healthcare monitoring systems. The model effectively captured both spatial and temporal dependencies in sensor data, improving prediction accuracy for dynamic health conditions. However, the complexity of the model increased computational requirements and energy consumption.

El-Sayed et al. (2022) introduced a hybrid GNN model combined with optimization techniques for healthcare monitoring. The system utilized feature selection and parameter tuning to improve model performance. While the approach enhanced accuracy, it increased computational overhead and training time.

Zhao et al. (2021) developed a blockchain-based secure architecture for wearable IoT monitoring systems integrated with graph-based learning. The framework ensured data integrity and secure communication. However, scalability and energy consumption remained challenges in large-scale deployments.

Fernandez et al. (2023) proposed a compressed Graph Neural Network using pruning and quantization techniques. The model reduced computational cost and energy consumption while maintaining acceptable accuracy. However, excessive compression could degrade model performance.

Kulkarni and Joshi (2022) introduced a hybrid GNN model combined with Bayesian learning for improved uncertainty estimation in healthcare monitoring. The system enhanced reliability and interpretability but increased computational complexity.

Comparative Table

No.	Author (Year)	GNN / Model Type	Optimization Used	Architecture	Accuracy Level	Energy Efficiency	Key Limitation
1	Wu et al. (2021)	GCN	Feature learning	IoT	High	Medium	High computation
2	Zhang et al. (2022)	GAT	Attention mechanism	IoT	High	Medium	High energy usage
3	Kumar et al. (2023)	GNN + RL	Reinforcement Learning	IoT	High	High	Complex training
4	Singh et al. (2021)	Routing Protocol	Energy optimization	WSN	Medium	Very High	No AI
5	Chen et al. (2022)	ST-GNN	Temporal modelling	IoT	Very High	Medium	High complexity
6	Li et al. (2022)	GNN + Edge	Edge optimization	Edge-IoT	High	High	Infrastructure need
7	Patel et al. (2023)	Pruned GNN	Model pruning	IoT	Medium	Very High	Accuracy loss
8	Ahmed et al. (2021)	GNN (Anomaly Detection)	Unsupervised learning	IoT	High	Medium	False positives
9	Kaur & Singh (2022)	GNN + CNN	Hybrid DL	IoT	Very High	Medium	High computation
10	Roy et al. (2023)	GNN + PSO	Optimization	IoT	High	High	Training overhead
16	Hassan et al. (2021)	Lightweight GCN	Model reduction	IoT	Medium	Very High	Reduced accuracy
17	Ibrahim et al. (2022)	GNN + Edge	Edge computing	Edge-IoT	High	High	Security issues
18	Patel et al. (2023)	Quantized GNN	Quantization	IoT	High	Very High	Approximation error
19	Roy et al. (2022)	GNN + RL	Adaptive learning	IoT	High	High	Training complexity
20	Kumar et al. (2021)	Routing Protocol	Energy-aware	WSN	Medium	Very High	No AI
21	Wang et al. (2023)	ST-GNN	Spatio-temporal learning	IoT	Very High	Medium	High computation
22	El-Sayed et al. (2022)	GNN + Optimization	Feature selection	IoT	High	Medium	Overhead
23	Zhao et al. (2021)	Blockchain + GNN	Secure architecture	IoT	High	Medium	Scalability
24	Fernandez et al. (2023)	Compressed GNN	Pruning + Quantization	IoT	High	Very High	Performance trade-off
25	Kulkarni & Joshi (2022)	Bayesian GNN	Probabilistic learning	IoT	Very High	Medium	High complexity

Comparative Analysis

The comparative analysis of the 30 studies reveals that hybrid Graph Neural Network (GNN)-based approaches are becoming increasingly important in wearable IoT healthcare monitoring systems. GNN models such as Graph Convolutional Networks, Graph Attention Networks, and spatio-temporal GNNs demonstrate superior performance in modelling complex relationships between sensor nodes and handling dynamic healthcare data. However, these models require high computational resources, which limits their deployment in resource-constrained wearable devices. To address these challenges, lightweight approaches such as quantized and pruned GNN models have been developed, significantly reducing computational complexity and energy consumption. While these methods improve efficiency, they may introduce slight reductions in accuracy. Adaptive optimization techniques, including reinforcement learning, particle swarm optimization, and evolutionary algorithms, enhance system adaptability and performance by dynamically adjusting model parameters. However, these techniques increase training time and computational overhead.

Energy efficiency is primarily achieved through Wireless Sensor Network (WSN) optimization techniques such as adaptive routing and clustering, as well as IoT architectures like edge and fog computing. These approaches reduce latency and energy consumption by processing data closer to the source. Blockchain-based architectures enhance data security and integrity but introduce scalability challenges. Overall, hybrid approaches integrating GNNs, adaptive algorithms, and energy-efficient WSN architectures provide the most effective solution for scalable, accurate, and energy-efficient wearable IoT monitoring systems.

Discussion

The integration of Graph Neural Networks (GNNs) with wearable IoT monitoring systems has significantly enhanced healthcare applications by enabling efficient modelling of complex sensor relationships. The reviewed studies indicate that GNN-based models provide high accuracy in analysing physiological data and detecting anomalies. However, their high computational requirements pose challenges for deployment in energy-constrained environments. Lightweight techniques such as quantization and pruning have emerged as effective solutions for reducing computational complexity and energy consumption. Adaptive optimization algorithms further improve system performance by enabling dynamic adjustment of network parameters. However, these methods introduce additional complexity and training overhead.

Energy-efficient WSN integration plays a crucial role in extending network lifetime and ensuring reliable data transmission. Techniques such as adaptive routing, clustering, and edge computing reduce energy consumption and latency. Additionally, blockchain and multi-layer security frameworks enhance data privacy and integrity but increase processing overhead. Overall, hybrid approaches combining GNNs, optimization techniques, and energy-efficient architectures are essential for developing scalable and reliable wearable IoT healthcare systems.

Conclusion

Wearable Internet of Things (IoT) technologies have transformed healthcare by enabling continuous monitoring and real-time analysis of physiological parameters. This review demonstrates that hybrid Graph Neural Network (GNN) architectures combined with adaptive algorithms and energy-efficient Wireless Sensor Networks (WSNs) significantly improve intelligent healthcare monitoring. Graph Convolutional Networks, Graph Attention Networks, and spatio-temporal GNNs effectively capture complex relationships among sensor nodes, enhancing prediction accuracy, anomaly detection, and clinical decision-making. Adaptive optimization techniques, including reinforcement learning and evolutionary algorithms, further improve network performance by dynamically optimizing communication and resource allocation. Energy-aware routing, clustering, edge computing, and fog computing reduce power consumption, communication overhead, and latency, thereby extending the operational lifetime of wearable devices. Despite these advances, challenges related to computational complexity, scalability, interoperability, and data security continue to hinder practical deployment. Future research should emphasize lightweight GNN models, explainable artificial intelligence, federated learning, and robust security frameworks to support efficient real-world implementation. Overall, hybrid GNN-based wearable IoT systems provide a scalable, reliable, and energy-efficient foundation for next-generation smart healthcare monitoring.

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