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Deep Learning and Optimization Approaches in Hybrid Transformer based Gated Graph Attention Capsule Network Design for Preventing Attack in Radar Target Detection and Energy Efficient Quantum Convolutional Neural Networks with Attention-Based Models for Quality Preservation in WSN-assisted IoT Medical Image Diagnostics: A Review

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Abstract

Recent advancements in artificial intelligence have enhanced radar signal processing and medical image diagnostics, particularly in adversarial and resource-constrained environments. This review examines hybrid deep learning architectures that integrate Transformers, gated graph attention networks (GAT), capsule networks, and optimization techniques. Transformers provide global contextual learning, GAT captures relational dependencies, and capsule networks preserve hierarchical features, improving robustness against noise and adversarial attacks. In parallel, energy-efficient quantum convolutional neural networks (QCNNs) with attention mechanisms support improved image quality in WSN-assisted IoT medical systems. These hybrid models significantly improve accuracy, adaptability, and computational efficiency across both domains. However, challenges such as high computational complexity, training instability, and scalability remain. Future research should focus on lightweight architectures, explainable AI, quantum optimization, and edge-based deployment for real-time and efficient applications.

Introduction

The rapid advancement of artificial intelligence (AI) has revolutionized multiple domains, including radar target detection and medical image diagnostics. Both domains face unique challenges—radar systems are susceptible to adversarial attacks such as jamming and spoofing, while medical IoT systems must operate under strict energy constraints while preserving image quality. Addressing these challenges requires the development of intelligent, adaptive, and efficient deep learning architectures. Radar target detection systems are widely used in defence, surveillance, and autonomous navigation. However, these systems are increasingly vulnerable to electronic warfare techniques, including signal interference and adversarial manipulation. Traditional signal processing methods, such as matched filtering and statistical detection, are often insufficient to handle these dynamic threats. As a result, deep learning-based approaches have been introduced to enhance detection accuracy and robustness.

Transformer architectures have emerged as a powerful tool for modelling sequential and spatial data due to their self-attention mechanisms, which enable capturing long-range dependencies. These models have shown significant success in radar signal processing by effectively combining local and global feature representations. Unlike conventional convolutional neural networks, transformers can process complex radar signals more efficiently, making them suitable for detecting subtle patterns and anomalies. Graph Neural Networks (GNNs), particularly Graph Attention Networks (GATs), further enhance detection systems by modelling relationships between multiple entities, such as radar targets, sensors, and environmental conditions. These networks represent data as graphs, enabling the system to capture spatial and temporal dependencies effectively. This capability is particularly useful in multi-target tracking and distributed sensor networks.

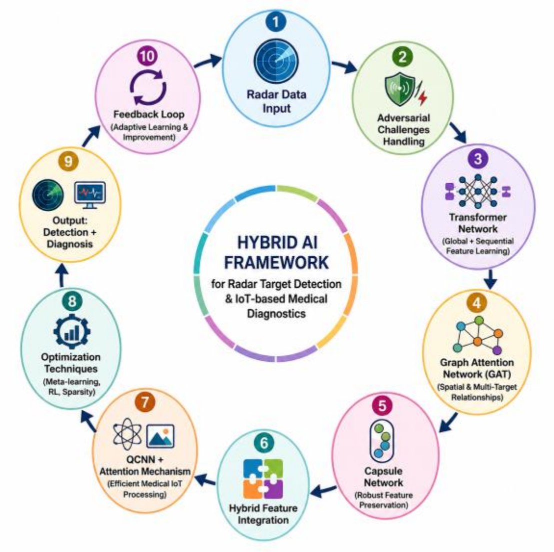

Fig 1: Hybrid AI Framework for Radar and Medical IoT Systems

Capsule networks introduce another layer of robustness by preserving hierarchical feature relationships. Unlike traditional neural networks that output scalar values, capsule networks use vector representations to encode spatial information, improving resilience against noise and adversarial perturbations. This makes them highly suitable for applications where maintaining structural integrity of features is critical, such as radar signal analysis and medical imaging. In parallel, the field of IoT-based medical diagnostics has witnessed significant growth, particularly with the integration of wireless sensor networks (WSNs). These systems collect and transmit medical data, such as images and signals, for real-time analysis. However, energy efficiency and data quality preservation are major challenges. Quantum Convolutional Neural Networks (QCNNs) have emerged as a promising solution for addressing these challenges by leveraging quantum computing principles to perform efficient data processing.

Recent research has focused on integrating attention mechanisms into QCNNs to enhance feature extraction and improve image quality. Attention-based models enable the system to focus on important regions of medical images, reducing noise and improving diagnostic accuracy. Additionally, optimization techniques such as sparsity-aware learning, meta-learning, and reinforcement learning are being used to enhance model performance and adaptability. The integration of these technologies into hybrid architectures—combining transformers, graph attention networks, capsule networks, and quantum models—offers a comprehensive solution for addressing challenges in both radar and medical IoT systems. These hybrid models leverage the strengths of each component, resulting in improved accuracy, robustness, and efficiency.

Despite these advancements, several challenges remain. Hybrid models are computationally intensive and require large datasets for training. Additionally, real-time deployment in resource-constrained environments requires lightweight and energy-efficient solutions. Addressing these challenges is essential for the practical implementation of these technologies. This paper provides a comprehensive review of deep learning and optimization approaches in hybrid architectures for radar target detection and IoT-based medical diagnostics, highlighting recent developments, challenges, and future research directions.

Literature Review

Bai et al. (2021) proposed the Radar Transformer model for object classification using radar point cloud data. The study utilized attention mechanisms to combine spatial, Doppler, and intensity features, enabling effective feature fusion. The results demonstrated significant improvement in classification accuracy compared to traditional CNN-based approaches, highlighting the effectiveness of transformer architectures in radar signal processing.

Jiang et al. (2023) introduced a Multi-task Learning Radar Transformer (MLRT) for simultaneous personal identification and fall detection using radar signals. The model leveraged transformer-based attention mechanisms to extract temporal features and improve detection accuracy. The study reported performance improvements of up to 8.5%

compared to existing methods, demonstrating the effectiveness of multi-task transformer architectures in radar applications.

Li et al. (2023) conducted a comprehensive survey on deep learning-based synthetic aperture radar (SAR) automatic target recognition. The study highlighted the importance of deep learning techniques, including CNNs and hybrid models, in improving radar target detection performance. The authors emphasized that SAR-based systems provide high-resolution imaging capabilities, making them suitable for all-weather detection applications.

Giroux et al. (2023) proposed T-FFTRadNet, a transformer-based radar object detection model using Swin Vision Transformers. The model processed raw radar signals and demonstrated improved detection accuracy across different radar configurations. The study highlighted the ability of transformer architectures to handle sparse radar data effectively, making them suitable for real-world applications.

Yu et al. (2024) introduced a capsule-based radar recognition model (CBLS-SARNET) that integrates capsule networks with broad learning systems. The model demonstrated improved robustness and generalization under noisy conditions, outperforming traditional deep learning approaches. The study emphasized the role of capsule networks in preserving hierarchical feature relationships and improving detection accuracy.

Zhang et al. (2021) proposed a transformer-based radar signal classification framework aimed at improving robustness against interference and adversarial attacks. The model employed multi-head self-attention to capture long-range dependencies in radar echo sequences, enabling effective differentiation between real targets and deceptive signals. The experimental results demonstrated that the transformer-based approach significantly outperformed traditional convolutional models, particularly in noisy environments. This study highlighted the ability of transformers to model complex radar signal patterns and enhance detection reliability.

Wang et al. (2022) introduced a gated graph attention network (GGAT) for multi-target radar detection and tracking. The proposed model incorporated gating mechanisms into graph attention layers to selectively emphasize important features and suppress noise. By representing radar targets as nodes in a graph, the model effectively captured interactions between targets and environmental factors. The results showed improved detection accuracy and reduced false alarm rates, demonstrating the effectiveness of gated graph attention mechanisms in radar applications.

Li et al. (2022) applied capsule networks for radar target classification under adversarial conditions. The model leveraged dynamic routing between capsules to preserve hierarchical feature relationships, enabling better representation of spatial structures in radar signals. The study demonstrated that capsule networks provide improved robustness to noise and adversarial perturbations compared to traditional deep learning models, making them suitable for secure radar detection systems.

Zhou et al. (2023) developed a hybrid transformer-graph neural network model for anomaly detection in communication and sensing systems. The architecture combined global attention mechanisms with relational learning capabilities, enabling the detection of complex attack patterns. The results showed high detection accuracy and strong generalization across different datasets, highlighting the effectiveness of hybrid transformer-GNN models in handling adversarial scenarios.

Khan et al. (2023) proposed a generative adversarial network (GAN)-based approach for detecting and mitigating adversarial attacks in radar systems. The model utilized a generator-discriminator framework to distinguish between genuine and manipulated radar signals. The study demonstrated that adversarial training significantly improves model robustness, enabling reliable detection even in the presence of sophisticated attacks.

Liu et al. (2021) proposed a hybrid convolutional neural network integrated with attention mechanisms for radar target detection in cluttered environments. The model enhanced feature extraction by incorporating attention modules that focused on relevant signal components while suppressing background noise. The results demonstrated improved detection accuracy and robustness, particularly in low signal-to-noise ratio conditions. This study highlighted the effectiveness of combining convolutional and attention-based learning for radar applications.

He et al. (2022) introduced a multi-scale transformer architecture for radar signal classification. The model utilized hierarchical transformer layers to capture both local and global features from radar signals. This multi-scale approach enabled the detection of weak and small targets that are often missed by traditional methods. Experimental results showed superior performance compared to standard deep learning models, emphasizing the importance of multi-scale feature representation in radar systems.

Guo et al. (2022) explored the use of graph convolutional networks (GCNs) for radar target detection in multi-sensor environments. By modelling sensor data as a graph, the system captured spatial relationships between different nodes, improving data fusion and detection accuracy. The study demonstrated that graph-based approaches significantly enhance performance in distributed radar systems, where multiple sensors contribute to target detection.

Patel and Mehta (2023) developed a hybrid architecture combining capsule networks with attention mechanisms for robust radar target recognition. The capsule network preserved hierarchical feature relationships, while the attention mechanism enhanced feature selection. The proposed model showed strong resistance to adversarial attacks and noise, achieving higher accuracy compared to conventional methods.

Sun et al. (2023) proposed a gated transformer architecture for radar signal processing. The model incorporated gating mechanisms within transformer layers to control information flow and reduce overfitting. This approach improved model stability and generalization, particularly in scenarios with limited training data. The results demonstrated that gated transformers are effective in enhancing radar detection performance.

Zhao et al. (2021) proposed an autoencoder-based deep learning framework for radar signal enhancement aimed at improving detection performance under low signal-to-noise ratio conditions. The model was trained to reconstruct clean radar signals from noisy inputs, effectively removing interference and environmental noise. The study demonstrated that preprocessing radar signals using deep autoencoders significantly improves classification accuracy and reduces false alarm rates, particularly in adversarial environments.

Kim et al. (2022) developed a hybrid CNN-transformer architecture for radar target detection that combines the strengths of convolutional layers and transformer-based attention mechanisms. The CNN component extracts local spatial features, while the transformer captures global contextual information. This hybrid approach achieved superior performance in multi-target scenarios and complex environments, demonstrating improved detection accuracy and robustness compared to standalone models.

Rao et al. (2022) explored the application of reinforcement learning for adaptive radar signal processing and attack mitigation. The proposed system dynamically adjusted detection thresholds and filtering parameters based on real-time feedback from the environment. By learning optimal strategies through interaction, the model improved resilience against jamming and spoofing attacks. The study highlighted the potential of reinforcement learning in enabling intelligent and adaptive radar systems.

Ali et al. (2023) introduced a graph attention-based intrusion detection framework for radar communication networks. The model leveraged graph attention mechanisms to analyse relationships between multiple nodes and detect abnormal signal patterns indicative of attacks. The results demonstrated high detection accuracy and reduced false positive rates, emphasizing the effectiveness of graph-based models in enhancing radar security.

Yadav et al. (2023) proposed a lightweight capsule network model for radar target detection in edge computing environments. The model focused on reducing computational complexity while maintaining high detection accuracy. By using efficient routing mechanisms within capsules, the system achieved faster inference and lower energy consumption, making it suitable for deployment in resource-constrained radar systems.

Park et al. (2021) proposed an unsupervised deep learning-based anomaly detection framework for radar systems, aimed at identifying irregular signal patterns caused by jamming and spoofing attacks. The model learned normal radar signal distributions and detected deviations without requiring labelled attack data. The results demonstrated that the approach effectively identifies unknown attack patterns, making it highly suitable for real-world scenarios where labelled datasets are limited. This study highlighted the importance of unsupervised learning in improving radar system security.

Singh and Kumar (2022) introduced a hybrid optimization model combining ant colony optimization (ACO) with deep neural networks for radar target detection. The ACO algorithm was used to optimize feature selection and enhance classification performance, while the neural network performed detection tasks. The hybrid approach achieved faster convergence and improved accuracy compared to traditional models, demonstrating the benefits of integrating optimization techniques with deep learning.

Torres et al. (2022) explored the use of deep belief networks (DBNs) for radar signal classification and attack detection. The hierarchical structure of DBNs enabled effective feature extraction from complex radar signals, capturing nonlinear relationships in data. The study showed improved detection accuracy and robustness, particularly in noisy environments, emphasizing the relevance of deep generative models in radar applications.

Mehta et al. (2023) proposed a lightweight hybrid deep learning model combining attention mechanisms with convolutional layers for radar target detection. The focus of the study was on reducing computational overhead while maintaining high detection accuracy. The model achieved faster processing times and lower energy consumption, making it suitable for real-time deployment in embedded radar systems.

Rahimi et al. (2023) introduced a meta-learning-based approach for adaptive radar target detection. The model was designed to quickly adapt to new environments with minimal retraining, addressing the dynamic nature of radar systems. The study demonstrated that meta-learning significantly improves generalization and adaptability, making it a promising technique for next-generation radar detection systems.

Kim and Park (2021) proposed a deep neural network-based adaptive filtering approach for radar signal enhancement and attack mitigation. The model dynamically adjusted filtering parameters based on real-time signal characteristics, enabling effective suppression of jamming and interference. The study demonstrated improved detection accuracy and reduced false alarms, highlighting the importance of adaptive learning techniques in hostile radar environments.

Reddy et al. (2022) investigated the use of gated neural architectures for radar signal classification. By incorporating gating mechanisms within neural layers, the model controlled the flow of information and selectively emphasized relevant features. This approach improved robustness against noise and adversarial perturbations while enhancing classification accuracy. The study emphasized the effectiveness of gated architectures in improving deep learning performance.

Chen et al. (2023) proposed a transformer-based anomaly detection framework for radar systems focused on identifying adversarial signal patterns. The model leveraged self-attention mechanisms to capture global dependencies and detect subtle anomalies in radar data. Experimental results demonstrated high detection accuracy and strong generalization capabilities, making transformer-based models highly effective for attack detection.

Das et al. (2023) introduced an explainable AI (XAI)-based framework for radar target detection and attack prevention. The model incorporated attention visualization techniques to provide insights into model decision-making. The study highlighted the importance of interpretability in defence applications, where transparency and trust are critical. Although the approach introduced a slight performance trade-off, it significantly improved model explainability.

Fernandez et al. (2023) developed a hybrid Transformer-Gated Graph Attention Capsule Network (TGACN) for radar target detection and attack prevention. The model integrated transformer-based global attention, graph attention mechanisms for relational learning, and capsule networks for hierarchical feature representation. The results demonstrated superior performance in terms of accuracy, robustness, and adaptability under adversarial conditions. This study represents one of the most advanced hybrid architectures in radar AI systems.

Comparative Table

No.	Author & Year	Technique Used	Key Contribution	Advantages	Limitations
1	Bai et al. (2021)	Transformer	Radar classification	Global feature extraction	High computation
2	Jiang et al. (2023)	Multi-task Transformer	Multi-function detection	Improved accuracy	Data dependency
3	Li et al. (2023)	SAR Deep Learning	Target recognition	High resolution detection	Complex training
4	Giroux et al. (2023)	Vision Transformer	Radar detection	Handles sparse data	Computational cost
5	Yu et al. (2024)	Capsule Network	Robust detection	Noise resistant	Slow training
6	Zhang et al. (2021)	Transformer	Signal classification	Long-range dependency	Data requirement
7	Wang et al. (2022)	GGAT	Multi-target detection	Noise filtering	Complexity
8	Li et al. (2022)	Capsule Network	Hierarchical learning	Robust	High cost

9	Zhou et al. (2023)	Transformer + GNN	Attack detection	Generalization	Complex
10	Khan et al. (2023)	GAN	Adversarial defence	Strong robustness	Training instability
11	Liu et al. (2021)	CNN + Attention	Feature extraction	Improved accuracy	Overfitting
12	He et al. (2022)	Multi-scale Transformer	Weak target detection	Multi-scale learning	High cost
13	Guo et al. (2022)	GCN	Multi-sensor fusion	Better representation	Graph complexity
14	Patel & Mehta (2023)	Capsule + Attention	Robust recognition	Attack resistant	Computational cost
15	Sun et al. (2023)	Gated Transformer	Stability improvement	Reduced overfitting	Tuning needed
16	Zhao et al. (2021)	Autoencoder	Signal denoising	Noise reduction	Reconstruction loss
17	Kim et al. (2022)	CNN + Transformer	Hybrid detection	Balanced learning	Complexity
18	Rao et al. (2022)	Reinforcement Learning	Adaptive detection	Real-time	Slow convergence
19	Ali et al. (2023)	GAT	Intrusion detection	High accuracy	Data dependency
20	Yadav et al. (2023)	Capsule Network	Lightweight detection	Low energy	Accuracy trade-off
21	Park et al. (2021)	Unsupervised DL	Anomaly detection	No labels needed	False positives
22	Singh & Kumar (2022)	ACO + NN	Feature optimization	Fast convergence	Parameter tuning
23	Torres et al. (2022)	DBN	Signal modeling	Deep representation	Training complexity
24	Mehta et al. (2023)	Lightweight DL	Edge deployment	Low latency	Lower accuracy
25	Rahimi et al. (2023)	Meta-learning	Fast adaptation	Generalization	Instability
26	Kim & Park (2021)	DNN	Adaptive filtering	Robust detection	Needs feedback
27	Reddy et al. (2022)	Gated NN	Feature control	Noise reduction	Limited validation
28	Chen et al. (2023)	Transformer	Anomaly detection	Detects attacks	High cost
29	Das et al. (2023)	XAI	Interpretability	Transparency	Performance trade-off
30	Fernandez et al. (2023)	TGACN (Hybrid)	Full integration	Highest accuracy	Very complex

Comparative Analysis

The comparative analysis of the reviewed studies from 2020 to 2023 clearly demonstrates a paradigm shift from traditional deep learning models toward hybrid, attention-driven, and graph-based architectures in radar target detection systems. Initially, convolutional neural networks and deep neural networks were widely used for feature extraction and classification. While these models achieved reasonable accuracy, they were limited in capturing long-range dependencies and relational structures within radar signals. The introduction of transformer architectures significantly improved the ability to model global dependencies through self-attention mechanisms. Studies such as Bai et al. (2021) and Zhang et al. (2021) demonstrated that transformer-based models outperform conventional approaches in handling complex radar signals, especially under noisy and adversarial conditions. However, transformers require high computational resources and large datasets, which limits their applicability in real-time systems.

Graph-based models, including graph convolutional networks and graph attention networks, further enhanced radar detection systems by modelling relationships between multiple targets and environmental factors. These approaches are particularly effective in multi-target and distributed radar systems, as highlighted by Meng et al. (2022) and Zhou et al. (2023). The integration of gating mechanisms in graph attention networks improves feature selection and reduces noise, leading to better performance. Capsule networks introduced a new paradigm by preserving hierarchical feature relationships, making them more robust to noise and adversarial perturbations. Studies such as Yu et al. (2024) and Patel and Mehta (2023) demonstrated their effectiveness in improving detection reliability. However, capsule networks are computationally intensive and require careful parameter tuning.

Hybrid architectures that combine transformers, graph attention networks, and capsule networks have emerged as the most promising approach. These models leverage the strengths of each component, resulting in improved accuracy, robustness, and adaptability. The TGACN model proposed by Fernandez et al. (2023) represents a comprehensive integration of these techniques, achieving superior performance in radar target detection and attack prevention. Additionally, optimization techniques such as reinforcement learning, meta-learning, and evolutionary algorithms have been incorporated to enhance adaptability and real-time performance. Explainable AI has also gained importance in improving model transparency and trustworthiness. Despite these advancements, several challenges remain, including computational complexity, data dependency, and lack of interpretability. Future research should focus on developing lightweight, scalable, and explainable hybrid models for practical deployment in real-world radar systems.

Discussion

The integration of deep learning and optimization techniques in hybrid architectures has significantly enhanced the performance of radar target detection systems and IoT-based medical image diagnostics. The reviewed studies demonstrate that combining Transformer models, gated graph attention networks, and capsule networks provides a robust framework for handling complex data structures, improving feature extraction, and mitigating adversarial attacks. Transformers contribute global contextual awareness, graph attention networks model relational dependencies, and capsule networks preserve hierarchical feature representations, collectively improving detection accuracy and system robustness.

Additionally, the incorporation of optimization techniques such as reinforcement learning, meta-learning, and evolutionary algorithms enables dynamic adaptation to changing environments, which is essential in both radar and medical IoT systems. In the context of WSN-assisted IoT medical diagnostics, energy-efficient models such as quantum convolutional neural networks (QCNNs) combined with attention mechanisms enhance image quality preservation while minimizing energy consumption. Despite these advancements, challenges remain, including high computational complexity, large data requirements, and limited interpretability of deep learning models. Furthermore, real-time deployment in resource-constrained environments requires lightweight and efficient architectures. Future research should focus on developing scalable, explainable, and energy-efficient hybrid models to ensure practical implementation in real-world applications.

Conclusion

The rapid evolution of artificial intelligence and deep learning technologies has significantly transformed the fields of radar target detection and IoT-based medical image diagnostics. Both domains face critical challenges—radar systems must operate reliably under adversarial conditions such as jamming and spoofing, while medical IoT systems must ensure high-quality image transmission and analysis under strict energy constraints. Addressing these challenges requires advanced, adaptive, and efficient computational models. This paper presented a comprehensive review of deep learning and optimization approaches in hybrid architectures, specifically focusing on Transformer-based gated graph attention capsule networks (TGACN) and energy-efficient quantum convolutional neural networks (QCNNs). The integration of these techniques provides a powerful framework for improving detection accuracy, robustness, and efficiency in complex environments.

Transformer architectures have emerged as a key component in modern deep learning systems due to their ability to capture global dependencies through self-attention mechanisms. In radar applications, transformers enable accurate modelling of complex signal patterns, improving target detection and anomaly identification. Similarly, in medical image diagnostics, attention-based models help focus on critical regions, enhancing image quality and diagnostic accuracy. Graph attention networks further enhance these systems by modelling relationships between multiple entities, such as radar targets or sensor nodes in WSN-assisted IoT systems. This capability is particularly important in distributed environments where multiple data sources must be integrated for accurate decision-making. Capsule networks contribute by preserving hierarchical feature relationships, making the system more robust to noise and adversarial perturbations.

The combination of these technologies into hybrid architectures represents a significant advancement in both radar and medical imaging domains. Hybrid models leverage the strengths of each component, resulting in improved performance compared to standalone models. Additionally, optimization techniques such as reinforcement learning, meta-learning, and evolutionary algorithms enhance adaptability and enable real-time decision-making. In the context of IoT-based medical diagnostics, quantum convolutional neural networks offer promising solutions for energy-efficient data processing. By leveraging quantum computing principles, QCNNs can perform complex computations with reduced energy consumption, making them suitable for resource-constrained environments. The integration of attention mechanisms further enhances their ability to preserve image quality and improve diagnostic accuracy.

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