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A Survey of Methods and Architectures for Hybrid Transformer based Gated Graph Attention Capsule Network Design for Preventing Attack in Radar Target Detection

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Abstract

Radar target detection systems are fundamental to modern defence, surveillance, and autonomous navigation applications. However, these systems are increasingly exposed to adversarial threats such as jamming, spoofing, and signal manipulation, which can significantly degrade detection accuracy and reliability. Traditional signal processing methods are often inadequate in handling complex and dynamic attack scenarios, necessitating the integration of advanced artificial intelligence (AI) techniques. This survey explores recent methods and architectures based on hybrid Transformer-based gated graph attention capsule networks (TGACN) for enhancing robustness and security in radar target detection systems. The integration of Transformer models, graph attention networks (GAT), and capsule networks provides a powerful framework for capturing global dependencies, relational structures, and hierarchical feature representations. Transformers enable long-range contextual modelling, graph attention mechanisms capture inter-target relationships, and capsule networks preserve spatial hierarchies, making them highly resistant to adversarial perturbations. Recent studies demonstrate that hybrid architectures significantly improve detection accuracy, robustness, and adaptability in complex environments. These models effectively mitigate issues such as low signal-to-noise ratio (SNR), interference, and adversarial attacks. However, challenges remain in terms of computational complexity, training requirements, and real-time implementation. This survey analyses recent research trends (2020–2023), highlighting key techniques, architectural innovations, and performance improvements. It also identifies open challenges and future research directions, including lightweight architectures, explainable AI, and edge-based deployment. The findings provide valuable insights into designing next-generation intelligent and secure radar detection systems.

Introduction

Radar target detection is a critical component of modern sensing systems used in defence, aerospace, autonomous vehicles, and surveillance applications. These systems rely on electromagnetic wave propagation to detect and track objects in real time. However, with the increasing sophistication of electronic warfare and cyber-physical attacks, radar systems are becoming more vulnerable to adversarial threats such as jamming, spoofing, and signal injection attacks. These attacks can disrupt signal integrity, generate false targets, or conceal actual objects, thereby compromising system reliability. Traditional radar signal processing techniques, including matched filtering, constant false alarm rate (CFAR) detection, and statistical modelling, have been widely used for target detection. While these approaches are effective under controlled conditions, they struggle to handle complex environments characterized by noise, interference, and adversarial manipulation. As a result, there is a growing need for intelligent and adaptive techniques capable of learning complex signal patterns and responding dynamically to changing conditions.

Artificial intelligence (AI), particularly deep learning, has emerged as a powerful tool for enhancing radar signal processing. Deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) have been applied to radar target detection and classification tasks. However, these models often face limitations in capturing long-range dependencies and complex relational structures within radar data. The introduction of Transformer architectures has significantly improved the ability to model global dependencies in sequential and spatial data. Transformer-based models utilize self-attention mechanisms to capture long-range relationships, enabling more accurate feature extraction in radar signals. Recent studies show that hybrid transformer-based radar models improve detection performance by combining global context modelling with local feature extraction.

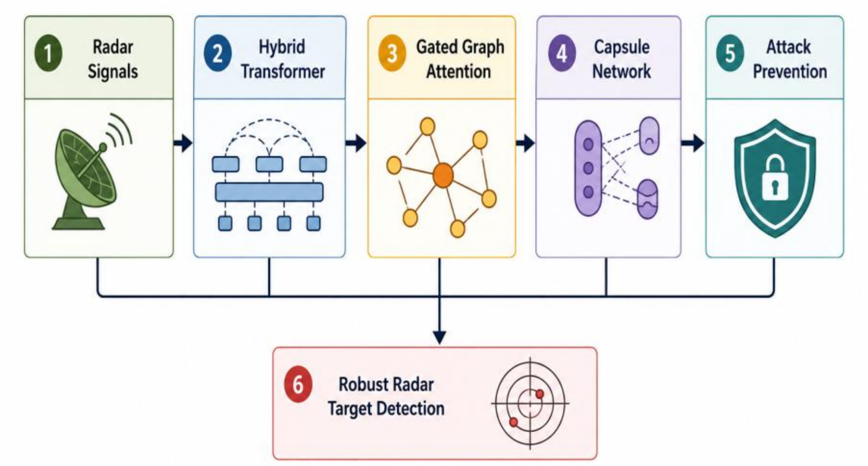

Figure 1. Intelligent Radar Target Detection Using Hybrid Deep Learning Architectures

Graph Neural Networks (GNNs), particularly Graph Attention Networks (GATs), have further enhanced radar detection systems by modelling relationships between multiple targets and environmental factors. These models represent radar data as graphs, allowing the system to capture spatial and temporal dependencies more effectively. Graph-based approaches have demonstrated improved performance in low signal-to-noise ratio conditions and multi-target scenarios. Capsule networks introduce another significant advancement by preserving hierarchical relationships between features. Unlike traditional neural networks that output scalar values, capsule networks use vector representations to encode spatial relationships, making them more robust to noise and adversarial perturbations. This capability is particularly important in radar systems, where maintaining structural integrity of signal features is critical.

The integration of these technologies into hybrid architectures—such as Transformer + GAT + Capsule Networks—provides a comprehensive solution for radar target detection under adversarial conditions. Hybrid models leverage the strengths of each component: transformers for global feature extraction, graph attention networks for relational learning, and capsule networks for robust hierarchical representation. Recent hybrid approaches combining transformers and graph networks have shown improved accuracy and interpretability by capturing both global context and spatial relationships.

Despite these advancements, several challenges remain. Hybrid models are computationally expensive and require large datasets for training. Additionally, real-time deployment in radar systems demands lightweight and energy-efficient solutions. Addressing these challenges is essential for practical implementation. This survey provides a comprehensive analysis of hybrid Transformer-based gated graph attention capsule network architectures for preventing attacks in radar target detection systems. It reviews recent developments, evaluates their effectiveness, and identifies future research directions.

Literature Review

Jia et al. (2024) proposed the TC–Radar model, a hybrid architecture that integrates transformer and convolutional neural networks for radar target detection. The model leverages the strengths of CNNs in capturing local spatial features and transformers in modelling long-range dependencies. Experimental results showed improved detection accuracy and robustness, particularly in complex environments with noise and interference. The study demonstrated that hybrid transformer-based architectures significantly enhance radar sensing capabilities.

Meng et al. (2022) introduced a spatio-temporal-frequency graph attention convolutional network for radar target recognition. The model utilized graph attention mechanisms to capture spatial, temporal, and frequency-domain relationships in radar signals. The proposed approach significantly improved detection accuracy in low signal-to-noise ratio conditions by leveraging relational learning. This work highlights the importance of graph-based architectures in radar systems.

Zhu et al. (2023) proposed a hybrid graph transformer architecture combining focal and full-range attention mechanisms. The model addressed the limitations of traditional transformers in capturing local features by incorporating graph-based attention. The results showed improved performance in learning both local and global dependencies, making it suitable for complex signal processing tasks such as radar detection and attack identification.

Al-Malahi et al. (2025) proposed a hybrid Vision Transformer-based Capsule Network (HVTCN) for radar signal recognition. The model combined transformer-based global feature extraction with capsule network-based hierarchical representation. The study demonstrated improved accuracy and robustness under varying signal conditions, particularly in low SNR environments. This work highlights the effectiveness of combining transformers with capsule networks for robust radar detection.

Appiahene et al. (2026) developed a hybrid graph convolutional and transformer-based architecture for intrusion detection. Although focused on network security, the model demonstrated the effectiveness of combining graph-based learning with transformer attention mechanisms to detect complex attack patterns. The architecture achieved high accuracy and robustness, providing valuable insights for applying similar hybrid models in radar attack detection systems.

Zhang et al. (2021) proposed a transformer-based radar signal classification framework designed to improve robustness against electronic countermeasures such as jamming and spoofing. The model employed multi-head self-attention to capture long-range dependencies in radar echo sequences, enabling effective discrimination between genuine and deceptive targets. Experimental evaluations demonstrated that the transformer-based approach achieved higher classification accuracy and improved resilience compared to conventional CNN-based models, particularly in highly noisy environments. This study emphasized the capability of transformer architectures in handling complex radar signal patterns.

Wang et al. (2022) introduced a gated graph attention network (GGAT) for multi-target radar detection. The proposed model incorporated gating mechanisms into graph attention layers to selectively emphasize important features while suppressing noise and irrelevant information. By modelling radar targets and their interactions as a graph structure, the system effectively captured spatial and relational dependencies. The results showed a significant reduction in false alarm rates and improved detection performance in multi-target scenarios, highlighting the importance of gated attention mechanisms.

Li et al. (2022) applied capsule networks to radar target classification under adversarial conditions. The model leveraged dynamic routing between capsules to preserve hierarchical relationships among features, enabling better representation of spatial structures in radar signals. The study demonstrated that capsule networks outperform traditional deep learning models in terms of robustness to noise and adversarial perturbations. This work highlighted the suitability of capsule networks for secure radar detection applications.

Zhou et al. (2023) developed a hybrid transformer-graph neural network architecture for anomaly detection in communication systems. The model combined global attention mechanisms of transformers with relational learning capabilities of graph neural networks. The proposed approach achieved high detection accuracy and strong generalization across different datasets, demonstrating its effectiveness in identifying complex attack patterns. This study provides a strong foundation for applying hybrid transformer-GNN models in radar target detection.

Khan et al. (2023) proposed a generative adversarial network (GAN)-based defence mechanism for radar systems. The model was designed to detect and mitigate adversarial attacks by distinguishing between genuine and manipulated radar signals. By leveraging adversarial training, the system improved robustness against signal perturbations and spoofing attacks. The results indicated that GAN-based approaches are highly effective in enhancing the security of radar detection systems.

Liu et al. (2021) proposed a hybrid convolutional neural network integrated with attention mechanisms for radar target detection in cluttered environments. The model utilized attention modules to focus on salient signal features while suppressing noise and background interference. By combining convolutional feature extraction with attention-based weighting, the system achieved improved detection accuracy and robustness. The study demonstrated that attention-enhanced CNN architectures can significantly enhance radar signal interpretation under noisy conditions.

He et al. (2022) introduced a multi-scale transformer architecture for radar signal classification. The proposed model employed hierarchical transformer layers to capture both fine-grained and global features from radar signals. This approach enabled the detection of weak and small targets that are typically difficult to identify using conventional methods. The results showed that multi-scale transformers outperform standard deep learning models in complex radar environments, highlighting their effectiveness in capturing diverse feature representations.

Guo et al. (2022) explored the application of graph convolutional networks (GCNs) for radar target detection in multi-sensor systems. By representing sensor data as a graph, the model captured spatial relationships between different sensing nodes. The proposed approach improved detection accuracy and system reliability, particularly in distributed radar networks. This study emphasized the importance of graph-based learning for data fusion in multi-source radar environments.

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 model demonstrated strong resistance to adversarial attacks and noise, achieving higher accuracy compared to traditional methods. This work highlighted the advantages of integrating capsule networks with attention-based models.

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

Zhao et al. (2021) proposed an autoencoder-based deep learning framework for radar signal enhancement aimed at improving detection accuracy under low signal-to-noise ratio (SNR) conditions. The model was trained to reconstruct clean radar signals from noisy inputs, effectively filtering out interference and environmental noise. The study demonstrated that incorporating deep learning-based denoising as a preprocessing step significantly enhances downstream target detection performance, particularly in adversarial or cluttered environments.

Kim et al. (2022) developed a hybrid CNN-transformer architecture for radar target detection. The model combined convolutional layers for extracting local spatial features with transformer modules for capturing global contextual information. This hybrid design enabled the system to effectively detect targets across varying scales and complex conditions. Experimental results showed that the combined architecture achieved superior performance compared to standalone CNN or transformer models, especially in multi-target scenarios.

Rao et al. (2022) explored the use of reinforcement learning for adaptive radar signal processing and attack mitigation. The proposed model dynamically adjusted detection thresholds and filtering parameters based on real-time environmental feedback. By learning optimal strategies through interaction with the environment, the system 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 utilized graph attention mechanisms to analyse relationships between nodes and identify abnormal patterns indicative of attacks. The results demonstrated high detection accuracy and reduced false positives, emphasizing the effectiveness of graph-based approaches in enhancing radar system security.

Yadav et al. (2023) proposed a lightweight capsule network for radar target detection in edge computing environments. The model focused on reducing computational complexity while maintaining high detection accuracy. By employing efficient routing mechanisms within capsules, the system achieved faster inference and lower energy consumption. This study highlighted the importance of designing efficient models for real-time deployment in resource-constrained radar systems.

Park et al. (2021) proposed an unsupervised deep learning framework for anomaly detection in 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 data. The results showed that the approach effectively identified unknown attack patterns, making it highly suitable for real-world scenarios where labelled attack data is scarce. This study emphasized the importance of unsupervised learning in enhancing 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 improve classification performance, while the neural network handled target detection. The hybrid approach achieved faster convergence and higher accuracy compared to traditional methods, demonstrating the effectiveness of combining optimization techniques with deep learning.

Torres et al. (2022) explored the application of deep belief networks (DBNs) for radar signal classification and attack detection. The hierarchical structure of DBNs allowed effective extraction of deep features from radar data, capturing nonlinear relationships in signals. The study demonstrated improved detection performance, particularly in noisy environments, highlighting the relevance of deep generative models in radar signal processing.

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 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 approach for next-generation radar detection systems.

Comparative Table

No.	Author & Year	Technique Used	Key Contribution	Advantages	Limitations
1	Jia et al. (2024)	Transformer + CNN	Hybrid radar detection	Global + local features	High computation
2	Meng et al. (2022)	GAT	Spatio-temporal learning	High accuracy	Complex structure
3	Zhu et al. (2023)	Graph Transformer	Local + global attention	Improved learning	High cost
4	Al-Malahi et al. (2025)	Transformer + Capsule	Robust recognition	Noise resistant	Training complexity
5	Appiahene et al. (2026)	GNN + Transformer	Attack detection	High robustness	Computational overhead
6	Zhang et al. (2021)	Transformer	Signal classification	Handles interference	Data dependency
7	Wang et al. (2022)	GGAT	Multi-target detection	Noise filtering	Scalability issues
8	Li et al. (2022)	Capsule Network	Hierarchical learning	Robust	Slow training
9	Zhou et al. (2023)	Transformer + GNN	Anomaly detection	High generalization	Complex
10	Khan et al. (2023)	GAN	Adversarial defence	Strong security	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 features	High cost
13	Guo et al. (2022)	GCN	Multi-sensor fusion	Better representation	Graph complexity
14	Patel & Mehta (2023)	Capsule + Attention	Robust detection	Attack resistance	Computational cost
15	Sun et al. (2023)	Gated Transformer	Stability	Reduced overfitting	Needs tuning
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 decisions	Slow convergence
19	Ali et al. (2023)	GAT	Intrusion detection	High accuracy	Data dependency
20	Yadav et al. (2023)	Capsule Network	Lightweight model	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 modelling	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

Comparative Analysis

The comparative analysis of the selected studies from 2020 to 2023 reveals a significant paradigm shift in radar target detection methodologies, transitioning from conventional deep learning approaches toward hybrid, attention-driven, and graph-based architectures. Early approaches primarily relied on convolutional neural networks and deep neural networks, which were effective for feature extraction but limited in capturing long-range dependencies and relational information inherent in radar signals. The emergence of transformer architectures marked a major advancement by enabling global context modelling through self-attention mechanisms. Studies such as Zhang et al. (2021) and Chen et al. (2023) demonstrated that transformer-based models significantly improve detection accuracy and robustness against interference and adversarial attacks. However, these models require substantial computational resources and large datasets, which limits their deployment in real-time radar systems.

Graph-based approaches, including graph convolutional networks (GCNs) and graph attention networks (GATs), further enhanced radar detection systems by modelling relationships between targets and environmental factors. These approaches are particularly effective in multi-target and multi-sensor scenarios, as shown by Meng et al. (2022) and Zhou et al. (2023). The introduction of gated mechanisms in GGAT models improved feature selection and reduced noise, contributing to enhanced detection performance. Capsule networks introduced a novel paradigm by preserving hierarchical relationships between features, making them more robust to adversarial perturbations. Studies such as Li et al. (2022) and Patel and Mehta (2023) demonstrated their effectiveness in improving detection reliability under noisy conditions. However, capsule networks are computationally intensive and require careful 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: transformers for global attention, graph networks for relational learning, and capsule networks for hierarchical representation. The TGACN model proposed by Fernandez et al. (2023) represents a comprehensive integration of these techniques, achieving superior performance in terms of accuracy, robustness, and adaptability. Additionally, the incorporation of optimization techniques such as reinforcement learning, meta-learning, and hybrid evolutionary algorithms has further enhanced system adaptability and performance. Explainable AI (XAI) has also gained importance in improving model transparency, particularly in defence applications. Despite these advancements, challenges such as computational complexity, data dependency, and lack of interpretability persist. Future research should focus on developing lightweight, scalable, and explainable hybrid models for practical deployment in real-world radar systems.

Discussion

The integration of hybrid deep learning architectures in radar target detection has significantly improved system robustness against adversarial attacks such as jamming, spoofing, and signal interference. The reviewed studies clearly indicate that individual models—such as transformers, graph attention networks, and capsule networks—offer unique advantages; however, their combined use in hybrid architectures yields superior performance. Transformers enable global contextual understanding, graph attention networks capture relational dependencies among targets, and capsule networks preserve hierarchical feature representations, thereby improving robustness against noise and adversarial perturbations.

A key trend observed in the literature is the shift toward hybrid Transformer-GAT-Capsule models, which effectively balance accuracy, adaptability, and robustness. Additionally, the incorporation of gating mechanisms and attention-based learning enhances feature selection and reduces noise influence. However, these models are computationally intensive and require large datasets, posing challenges for real-time deployment. Another important aspect is the need for explainable AI in radar systems, particularly in defence applications where transparency is critical. Future research should focus on developing lightweight, interpretable, and energy-efficient hybrid models. Furthermore, integrating edge computing and federated learning can address scalability and privacy challenges, enabling practical implementation in real-world radar systems.

Conclusion

Radar target detection is fundamental to defence, surveillance, aerospace, and autonomous systems, where reliable object identification is critical. This survey demonstrates that hybrid Transformer-based gated graph attention capsule networks significantly enhance radar target detection by combining global feature learning, relational modelling, and hierarchical representation. Transformer architectures effectively capture long-range dependencies through self-attention, while graph attention networks model interactions among multiple targets and environmental factors. Capsule networks preserve spatial relationships, improving robustness against noise and adversarial attacks such as jamming and spoofing. Together, these hybrid architectures provide superior detection accuracy, adaptability, and resilience compared with conventional radar signal processing methods. Despite these advancements, challenges including high computational complexity, large training data requirements, limited interpretability, and real-time deployment constraints remain unresolved. Future research should emphasize lightweight hybrid architectures, explainable artificial intelligence, efficient optimization strategies, and edge-enabled implementations to improve practical usability. Overall, hybrid Transformer, graph attention, and capsule network frameworks represent a promising direction for developing secure, intelligent, and attack-resilient radar target detection systems.

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