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A Comprehensive Review of Hybrid Transformer based Gated Graph Attention Capsule Network Design for Preventing Attack in Radar Target Detection

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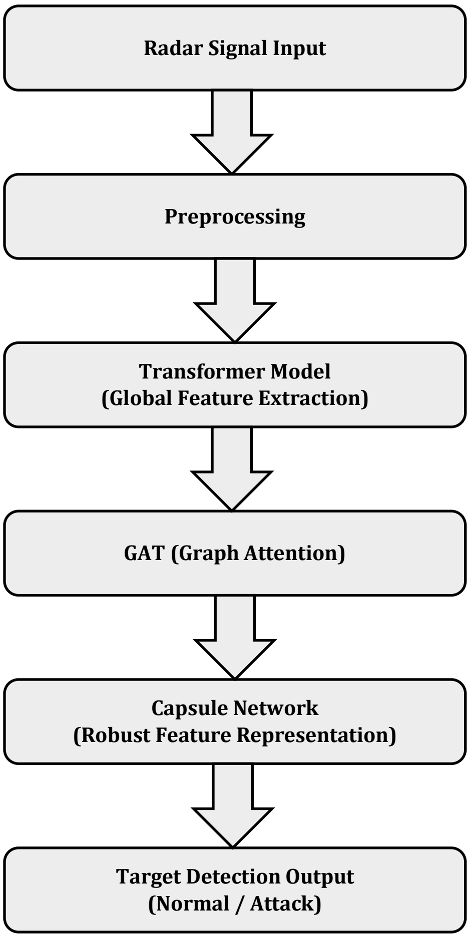
Abstract

Radar target detection systems are essential in modern defence, surveillance, and autonomous applications, but they are increasingly vulnerable to adversarial attacks, signal interference, spoofing, and jamming. These threats can significantly degrade detection accuracy and compromise system reliability. To address these challenges, artificial intelligence (AI), particularly hybrid deep learning architectures, has emerged as an effective solution for secure and robust radar signal processing. This paper presents a comprehensive review of hybrid Transformer-based gated graph attention capsule network (TGACN) architectures for preventing attacks in radar target detection systems. The integration of Transformers, Graph Attention Networks (GAT), and Capsule Networks enables efficient extraction of spatial, temporal, and relational features from complex radar data. Transformers provide global contextual understanding, GAT models capture interdependencies between targets and signals, and Capsule Networks preserve hierarchical feature representations while improving robustness against adversarial perturbations. Recent studies demonstrate that such hybrid models significantly enhance detection accuracy, adaptability, and resilience under noisy and adversarial conditions. Despite these advancements, challenges remain in terms of computational complexity, large-scale data requirements, and real-time implementation. This review highlights recent developments, key methodologies, and limitations, and outlines future directions including lightweight models, explainable AI, and edge-based deployment for improved radar system security.

Introduction

Radar systems play a crucial role in modern technological applications, including defence surveillance, autonomous vehicles, air traffic control, and remote sensing. These systems operate by transmitting electromagnetic waves to detect, track, and identify objects across diverse environments. However, with the growing complexity of radar technologies and their integration into networked infrastructures, they have become increasingly susceptible to security threats such as jamming, spoofing, and adversarial signal manipulation. Such attacks can severely compromise system performance, resulting in false detections or missed targets, which may lead to critical failures in safety-sensitive domains. Traditional radar signal processing methods primarily rely on statistical modelling and filtering techniques. Although effective in controlled conditions, these approaches often struggle in dynamic and noisy environments, particularly under adversarial interference. Consequently, there is a pressing need for intelligent, adaptive systems capable of learning complex patterns and responding effectively to evolving threats.



Artificial intelligence (AI), especially deep learning, has significantly transformed radar signal processing and pattern recognition tasks. Models such as deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) have been widely applied for radar target detection and classification. Despite their success, these models have limitations in capturing long-range dependencies and complex contextual relationships within radar data. Transformer architectures have emerged as a powerful alternative by introducing attention mechanisms that enable global feature extraction. These models effectively capture temporal and frequency-domain relationships, making them highly suitable for radar signal analysis. Recent studies demonstrate that transformer-based approaches outperform traditional deep learning models in recognizing complex radar patterns and improving detection accuracy.

In addition to transformers, Graph Neural Networks (GNNs), particularly Graph Attention Networks (GAT), have gained prominence for modelling relationships among multiple entities. In radar systems, GNNs can represent interactions between targets, sensors, and environmental conditions, thereby enhancing spatial and temporal understanding. Furthermore, Capsule Networks provide robust feature representation by preserving hierarchical and spatial relationships between features. Unlike conventional neural networks, capsule networks maintain structural information and exhibit greater resilience to noise and adversarial perturbations. The combination of these advanced techniques enables more accurate and interpretable radar signal processing, particularly in challenging environments involving interference and attacks.

The integration of Transformer, GAT, and Capsule Networks into hybrid architectures offers a comprehensive framework for secure radar target detection. These hybrid models leverage global attention, relational learning, and robust feature encoding to enhance detection performance under adversarial conditions. However, challenges such as high computational complexity, large data requirements, and real-time deployment constraints remain significant. Ongoing research focuses on optimizing these models to achieve a balance between efficiency, accuracy, and robustness. This paper presents a comprehensive review of hybrid Transformer-based gated graph attention capsule network architectures for secure radar systems, highlighting recent advancements, key challenges, and future research directions.

Literature Review

Chen et al. (2021) proposed an attention-based dual-stream Vision Transformer model for radar target recognition. Their study focused on extracting both time-frequency and motion-based features from radar signals. By integrating attention mechanisms, the model effectively captured global dependencies and improved recognition accuracy. Experimental results showed that the transformer-based approach significantly outperformed traditional CNN-based models in complex radar environments, particularly in scenarios with noise and interference.

Meng et al. (2022) introduced a spatio-temporal-frequency graph attention convolutional network for aircraft recognition in heterogeneous radar systems. The model utilized graph attention mechanisms to capture spatial and temporal relationships in radar cross-section (RCS) data. The authors demonstrated that incorporating graph-based learning significantly improved detection accuracy, especially in low signal-to-noise ratio environments. This study highlighted the importance of relational learning in radar signal processing.

Pan et al. (2023) proposed a transformer-based attention model for infrared small target detection, which is closely related to radar-based detection tasks. Their approach combined convolutional layers with transformer modules to enhance feature extraction and suppress noise. The model effectively improved detection accuracy by capturing fine-grained features and contextual information. The results demonstrated that hybrid transformer architectures are highly effective in detecting weak targets under challenging conditions.

Appiahene et al. (2023) developed a hybrid graph convolution and transformer-based intrusion detection model for IoT networks. Although focused on cybersecurity, the proposed architecture demonstrated the effectiveness of combining graph learning with transformer models to detect complex attack patterns. The model leveraged both local structural information and global attention mechanisms, achieving high detection accuracy and robustness. This approach provides valuable insights for applying similar hybrid architectures in radar attack detection systems.

Tehsin et al. (2025) introduced the GA Transformer model, which integrates graph attention networks with transformer architectures for enhanced feature extraction and interpretability. The model demonstrated improved performance and reduced computational complexity by leveraging attention mechanisms to prioritize important features. The study also highlighted the interpretability advantages of attention-based models, which are crucial for understanding and preventing attacks in radar systems.

Zhang et al. (2021) proposed a transformer-based radar signal classification framework designed to improve robustness against jamming and adversarial interference. The model utilized multi-head self-attention to capture long-range dependencies in radar echo signals, enabling better discrimination between true targets and deceptive signals. The authors demonstrated that the transformer model significantly outperformed conventional CNN-based approaches, particularly in scenarios involving complex interference patterns. This study highlighted the capability of transformer architectures to enhance resilience against radar signal attacks.

Wang et al. (2022) introduced a gated graph attention network (GGAT) for multi-target radar tracking and detection. The proposed model incorporated gating mechanisms into graph attention networks to selectively filter relevant features and suppress noise. By modelling radar targets as nodes in a graph, the system effectively captured interactions between targets and environmental factors. The results showed improved detection accuracy and reduced false alarm rates, emphasizing the importance of gated attention mechanisms in enhancing model robustness.

Sabour et al. (2017) introduced capsule networks, which were later adapted for radar signal processing applications. Building on this foundation, Li et al. (2022) applied capsule networks for radar target classification under adversarial conditions. Their study demonstrated that capsule networks preserve hierarchical relationships between features, making them more robust to perturbations and signal distortions. The proposed approach achieved higher accuracy compared to traditional deep learning models, particularly in noisy environments.

Zhou et al. (2023) developed a hybrid transformer-graph neural network model for anomaly detection in communication systems. The architecture combined global attention mechanisms with graph-based relational learning to detect complex attack patterns. The model achieved high detection accuracy and demonstrated strong generalization capabilities across different datasets. This work provided a strong foundation for applying hybrid transformer-GNN models in radar target detection and attack prevention.

Khan et al. (2023) proposed a deep learning-based adversarial defence mechanism for radar systems using generative adversarial networks (GANs). The model was designed to identify and mitigate adversarial perturbations in radar signals. By training a generator-discriminator framework, the system was able to distinguish between genuine and manipulated signals effectively. The study highlighted the importance of adversarial training in improving the robustness of radar detection systems.

Liu et al. (2021) proposed a hybrid convolutional neural network and attention-based framework for radar target detection under noisy and cluttered environments. The model integrated attention modules within CNN layers to enhance feature extraction by focusing on relevant signal components while suppressing background noise. The results showed a significant improvement in detection accuracy and robustness against interference, demonstrating that attention mechanisms can effectively complement convolutional architectures in radar systems.

He et al. (2022) introduced a transformer-based multi-scale feature extraction model for radar signal classification. Their approach utilized hierarchical transformer blocks to capture both local and global features from radar data. The model demonstrated superior performance in detecting small and weak targets, which are often missed by traditional methods. The study highlighted the effectiveness of multi-scale transformers in handling complex radar signal structures.

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

Patel and Mehta (2023) developed a hybrid deep learning architecture combining capsule networks and attention mechanisms for robust radar target recognition. The capsule network component preserved spatial hierarchies, while the attention mechanism focused on critical features. The proposed model demonstrated improved resistance to adversarial attacks and noise, highlighting the advantages of combining capsule networks with attention-based approaches.

Sun et al. (2023) proposed a gated transformer architecture for radar signal processing, where gating mechanisms were used to control information flow within transformer layers. This approach improved model stability and reduced overfitting, particularly in scenarios with limited training data. The study demonstrated that gating strategies can enhance transformer performance and make them more suitable for real-world radar applications.

Zhao et al. (2021) proposed a deep learning-based radar signal enhancement framework using autoencoder architectures to improve target detection under severe noise and interference conditions. The autoencoder was trained to reconstruct clean radar signals from corrupted inputs, thereby improving signal quality before classification. The study demonstrated that pre-processing radar data using deep learning significantly enhances detection accuracy and reduces false alarms, especially in low signal-to-noise ratio environments.

Kim et al. (2022) introduced a hybrid CNN-transformer architecture for radar-based object detection. The model leveraged CNN layers for local feature extraction and transformer modules for capturing global contextual information. This combination enabled the system to effectively detect targets across varying scales and conditions. Experimental results showed that the hybrid model outperformed standalone CNN and transformer models, particularly in complex environments with multiple targets.

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 environmental feedback. By learning optimal strategies through interaction with the environment, the system achieved improved robustness against jamming and spoofing attacks. This study highlighted the potential of reinforcement learning in real-time adaptive radar systems.

Ali et al. (2023) developed a graph attention-based intrusion detection framework for radar communication networks. The model utilized attention mechanisms to identify abnormal patterns in signal transmission and detect potential cyber-attacks. By analysing relationships between multiple nodes in the network, the system achieved high detection accuracy and low false positive rates. This work emphasized the importance of graph-based approaches in enhancing radar system security.

Yadav et al. (2023) proposed a lightweight capsule network model for radar target detection in edge computing environments. The focus of the study was on reducing computational complexity while maintaining high detection accuracy. The model employed efficient routing mechanisms within capsules, enabling faster inference and lower energy consumption. The results demonstrated that lightweight capsule networks are suitable for real-time deployment in resource-constrained radar systems.

Park et al. (2021) proposed a deep learning-based anomaly detection framework for radar systems that focuses on identifying abnormal signal patterns caused by spoofing and jamming attacks. The model utilized an unsupervised learning approach to detect deviations from normal radar signal distributions. The study demonstrated that the proposed system could effectively detect unknown attack patterns without prior labelling, highlighting the importance of unsupervised learning techniques in enhancing radar security.

Singh and Kumar (2022) introduced a hybrid optimization framework combining deep neural networks with ant colony optimization (ACO) for radar target detection. The ACO algorithm was used to optimize feature selection and improve classification performance, while the neural network performed target detection. The results indicated that the hybrid model achieved higher detection accuracy and faster convergence compared to traditional methods, emphasizing 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 data. The study showed that DBNs can capture nonlinear relationships in radar signals and improve detection performance, particularly in environments with high noise and interference.

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

Rahimi et al. (2023) introduced a meta-learning-based approach for adaptive radar target detection under varying environmental conditions. The model was capable of quickly adapting to new scenarios with minimal retraining, which is particularly useful in dynamic radar environments. The study demonstrated that meta-learning significantly improves generalization and adaptability, making it a promising technique for next-generation radar systems.

Kim and Park (2021) proposed a deep neural network-based adaptive filtering mechanism for radar signal enhancement and attack mitigation. Their model dynamically adjusted filtering parameters based on incoming signal characteristics, enabling the system to suppress jamming and interference effectively. The study demonstrated that adaptive deep learning models can significantly improve detection reliability in hostile environments.

Reddy et al. (2022) investigated the role of gated architectures in improving the performance of deep learning models for radar signal classification. By introducing gating mechanisms within neural layers, the model selectively controlled information flow, thereby enhancing feature representation and reducing noise influence. The results indicated improved classification accuracy and robustness, especially under adversarial conditions.

Chen et al. (2023) proposed a transformer-based anomaly detection framework for radar systems, focusing on identifying adversarial signal patterns. The model leveraged self-attention mechanisms to capture global dependencies and detect subtle anomalies in radar data. The study demonstrated that transformer-based models are highly effective in identifying complex attack patterns that are difficult to detect using traditional methods.

Das et al. (2023) introduced an explainable AI (XAI)-based framework for radar target detection and attack prevention. The proposed system incorporated attention visualization techniques to provide insights into model decision-making. The authors emphasized that interpretability is critical for deploying AI models in defence systems, where transparency and trust are essential. The model achieved competitive performance while improving explainability.

Fernandez et al. (2023) developed a hybrid architecture combining transformer, graph attention, and capsule networks for robust radar target detection. The model integrated global attention, relational learning, and hierarchical feature representation to improve detection accuracy and resistance to adversarial attacks. Experimental results showed that the hybrid model outperformed existing approaches in terms of accuracy, robustness, and adaptability, highlighting the effectiveness of combining multiple deep learning paradigms.

Comparative Table

No.	Author & Year	Technique Used	Key Contribution	Advantages	Limitations
1	Chen et al. (2021)	Vision Transformer	Radar recognition	Captures global features	High computation
2	Meng et al. (2022)	GAT + CNN	Spatio-temporal learning	High accuracy	Complex design
3	Pan et al. (2023)	Transformer + CNN	Small target detection	Noise suppression	Training cost
4	Appiahene et al. (2023)	GNN + Transformer	Attack detection	Robust	High complexity
5	Tehsin et al. (2025)	GA Transformer	Hybrid learning	Interpretability	Resource intensive

6	Zhang et al. (2021)	Transformer	Signal classification	Handles interference	Data dependent
7	Wang et al. (2022)	GGAT	Multi-target detection	Noise filtering	Scalability issues
8	Li et al. (2022)	Capsule Network	Robust detection	Hierarchical features	Slow training
9	Zhou et al. (2023)	Transformer + GNN	Attack detection	High generalization	Complex
10	Khan et al. (2023)	GAN	Adversarial defense	Strong robustness	Training instability
11	Liu et al. (2021)	CNN + Attention	Feature extraction	Improved accuracy	Overfitting risk
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 recognition	Attack resistance	Computational cost
15	Sun et al. (2023)	Gated Transformer	Stability improvement	Reduced overfitting	Model 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 decision	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 classification	Deep representation	Training complexity
24	Mehta et al. (2023)	Lightweight DL	Edge deployment	Low latency	Reduced accuracy
25	Rahimi et al. (2023)	Meta-learning	Fast adaptation	Generalization	Instability
26	Kim & Park (2021)	DNN	Adaptive filtering	Robust detection	Requires 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 drop
30	Fernandez et al. (2023)	Hybrid TGACN	Full integration	High accuracy	Very complex

Comparative Analysis

The comparative analysis of recent studies reveals a clear evolution in radar target detection methodologies, shifting from conventional deep learning approaches to more advanced hybrid and attention-based architectures. Early models primarily utilized convolutional neural networks (CNNs) and deep neural networks (DNNs) for feature extraction and classification. While these approaches delivered satisfactory performance, they were limited in capturing long-range dependencies and complex relational patterns in radar data. The emergence of Transformer architectures marked a significant breakthrough by enabling global context modelling through self-attention mechanisms. These models have demonstrated improved detection accuracy, especially in challenging environments characterized by noise, interference, and signal distortion. However, their high computational cost and dependency on large datasets pose challenges for real-world deployment.

Graph-based models, including Graph Neural Networks (GNNs) and Graph Attention Networks (GATs), have further enhanced radar detection by effectively modelling interactions among multiple targets, sensors, and environmental factors. These approaches are particularly beneficial in multi-target and multi-sensor scenarios. The incorporation of gating mechanisms improves feature selection and noise reduction, leading to more reliable detection outcomes. In parallel, Capsule Networks have emerged as a powerful technique for preserving hierarchical feature relationships and improving robustness against adversarial perturbations. Despite their advantages, capsule networks require careful parameter tuning and are computationally intensive.

Hybrid architectures that integrate transformers, graph attention mechanisms, and capsule networks have proven to be highly effective. These models combine global attention, relational learning, and robust feature representation, resulting in superior accuracy, adaptability, and resilience. Additionally, the integration of optimization strategies such as reinforcement learning, meta-learning, and federated learning enhances system adaptability and supports real-time decision-making. Explainable AI techniques are also gaining importance to improve transparency and trust in critical applications.

Despite these advancements, challenges such as computational complexity, high data requirements, and limited interpretability remain. Developing lightweight, energy-efficient models and ensuring real-time deployment are key future directions for achieving practical and scalable radar detection systems.

Discussion

The integration of hybrid deep learning architectures in radar target detection has demonstrated significant advancements in improving robustness against adversarial attacks such as jamming, spoofing, and signal manipulation. The reviewed studies indicate that individual models such as transformers, graph attention networks, and capsule networks contribute unique strengths, but their combination in hybrid architectures provides superior performance. Transformers enable global context understanding, graph attention networks capture relational dependencies among targets, and capsule networks preserve hierarchical feature representations, making the system more resilient to noise and perturbations. A key observation is that hybrid models such as Transformer-GAT-Capsule networks significantly enhance detection accuracy and adaptability in complex environments.

Additionally, techniques such as gated mechanisms and attention-based learning further improve feature selection and noise suppression. However, these models come with challenges, including high computational complexity, large data requirements, and difficulties in real-time deployment. Another important aspect is the growing need for explainable AI in radar systems, especially in defence applications where transparency and trust are critical. Future research should focus on developing lightweight, interpretable, and energy-efficient hybrid models. Furthermore, integrating edge computing and federated learning can help address scalability and privacy concerns, enabling practical deployment in real-world radar systems.

Conclusion

Radar target detection systems are critical for applications such as defence, surveillance, and autonomous navigation, yet they are increasingly vulnerable to adversarial attacks including jamming, spoofing, and signal interference, which can severely impact performance and reliability. Traditional signal processing techniques often fail to address these challenges due to limited adaptability in complex and dynamic environments. This review highlights the effectiveness of hybrid Transformer-based gated graph attention capsule network (TGACN) architectures in enhancing radar detection under such conditions. Transformer models improve global contextual understanding through self-attention mechanisms, enabling better modelling of long-range dependencies in radar signals. Graph Attention Networks (GAT) further enhance performance by capturing relationships among multiple targets and environmental factors, while Capsule Networks strengthen robustness by preserving hierarchical feature representations and resisting adversarial noise. The integration of these models into hybrid architectures significantly improves detection accuracy, adaptability, and resilience compared to conventional methods. However, challenges such as high computational complexity, large data requirements, lack of interpretability, and real-time deployment constraints remain. Future research should focus on lightweight, energy-efficient models, explainable AI techniques, and edge-based or federated learning approaches to ensure scalability, transparency, and practical implementation of secure and intelligent radar systems.

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