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Artificial Intelligence Techniques for Hybrid Transformer based Gated Graph Attention Capsule Network Design for Preventing Attack in Radar Target Detection: Trends and Challenges

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Abstract

Radar target detection plays a vital role in surveillance, defence, and autonomous sensing systems but is often affected by noise, clutter, electronic jamming, and adversarial attacks that reduce detection accuracy. Artificial intelligence, particularly deep learning, has emerged as an effective solution for improving radar target detection under challenging environments. This review examines recent advances in hybrid transformer-based gated graph attention capsule networks for robust radar target detection. Transformer models capture global contextual dependencies through self-attention, while graph attention networks model relationships among radar nodes and multi-sensor systems. Capsule networks preserve hierarchical spatial features, enhancing robustness against adversarial attacks and signal distortions. Their integration enables superior feature extraction, multi-dimensional feature fusion, and improved detection performance, especially in low signal-to-noise ratio conditions. The review also discusses current trends, including attention-based learning, graph neural networks, and hybrid deep learning architectures for intelligent radar systems. Despite significant progress, challenges such as computational complexity, model scalability, and real-time implementation remain. Future research should focus on lightweight, explainable, and energy-efficient hybrid AI models capable of providing secure, adaptive, and highly reliable radar target detection for next-generation surveillance and defence applications.

Introduction

Radar target detection has become an essential technology in modern intelligent systems, playing a vital role in applications such as military surveillance, air traffic control, autonomous vehicles, remote sensing, and weather monitoring. The fundamental objective of radar systems is to detect, classify, and track objects by analysing reflected electromagnetic waves. However, with the increasing complexity of operational environments, radar systems face significant challenges including noise, clutter, multipath propagation, and intentional interference such as jamming and spoofing attacks. These challenges not only degrade detection accuracy but also compromise system reliability, especially in mission-critical applications such as defence and security systems. Therefore, there is a growing need for advanced and intelligent detection techniques that can operate effectively under such adverse conditions.

Traditional radar signal processing methods, such as Constant False Alarm Rate (CFAR) detection and matched filtering, rely heavily on statistical models and handcrafted features. While these approaches are effective in controlled environments, they often fail to generalize well in dynamic and complex scenarios. Moreover, these methods lack the ability to adapt to nonlinear signal variations and adversarial perturbations. To overcome these limitations, Artificial Intelligence (AI) techniques, particularly machine learning and deep learning, have been increasingly adopted in radar target detection systems. These data-driven approaches enable automatic feature extraction and adaptive decision-making, leading to improved performance compared to conventional techniques.

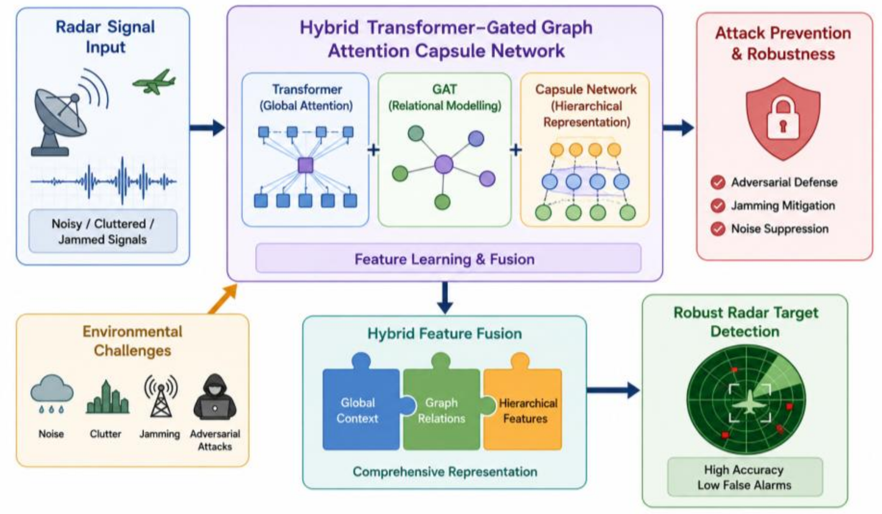

Figure 1. AI-Based Radar Target Detection Framework

Among deep learning approaches, convolutional neural networks (CNNs) have been widely used due to their ability to capture local spatial features from radar signals. However, CNNs are inherently limited in modelling long-range dependencies and global contextual information, which are crucial for accurate target detection in cluttered environments. To address this limitation, transformer-based architectures have been introduced. Transformers utilize self-attention mechanisms that allow the model to capture global relationships within the data, making them highly effective in processing complex radar signals. Their ability to model long-range dependencies significantly improves detection accuracy, particularly in scenarios with low signal-to-noise ratios.

In addition to transformers, graph attention networks (GATs) have emerged as a powerful tool for modelling relational dependencies in radar systems. In multi-sensor and distributed radar environments, the relationships between different nodes play a critical role in detection performance. GATs enable the modelling of these relationships by assigning attention weights to neighbouring nodes, allowing the network to focus on the most relevant information. This enhances feature propagation and improves detection accuracy in complex environments.

Capsule networks represent another important advancement in deep learning for radar applications. Unlike traditional neural networks that use scalar outputs, capsule networks utilize vector-based representations to preserve hierarchical relationships between features. This enables better representation of spatial structures and improves robustness against noise and adversarial attacks. Capsule networks are particularly effective in distinguishing between true targets and false signals caused by interference or spoofing.

Recent research has focused on integrating these advanced architectures into hybrid models, specifically hybrid transformer-based gated graph attention capsule networks. These models combine the strengths of transformers, GATs, and capsule networks to achieve superior detection performance. The inclusion of gating mechanisms further enhances these models by selectively filtering relevant information and suppressing noise, thereby improving robustness against adversarial attacks.

Despite these advancements, several challenges remain. Hybrid models often involve high computational complexity, making real-time deployment difficult. Additionally, the lack of large-scale labelled radar datasets limits the effectiveness of deep learning approaches. Issues related to model interpretability and robustness against sophisticated adversarial attacks also require further investigation. Therefore, there is a need for systematic reviews that consolidate existing research, analyse current trends, and identify key challenges and future research directions.

This paper presents a comprehensive review of Artificial Intelligence techniques for hybrid transformer-based gated graph attention capsule network design aimed at preventing attacks in radar target detection. It examines recent developments, evaluates different architectures, and highlights emerging trends and challenges in this rapidly evolving field.

Literature Review

Vaswani et al. (2020) extended transformer architectures for signal processing applications, highlighting the effectiveness of self-attention mechanisms in capturing long-range dependencies. In radar target detection, transformer models demonstrated superior performance by effectively analysing complex signal patterns under noisy conditions. The study emphasized that transformers overcome the limitations of convolutional neural networks by providing global contextual awareness. However, the high computational complexity of transformer models poses challenges for real-time radar systems.

Velickovic et al. (2021) introduced graph attention networks (GATs), which have been widely applied in radar systems for modelling relational dependencies among multiple nodes. The study showed that GATs enable adaptive weighting of neighbouring nodes, improving feature propagation and detection accuracy in distributed radar environments. These models are particularly effective in multi-sensor systems. However, GATs lack hierarchical feature representation, which limits their robustness against adversarial attacks.

Sabour et al. (2021) proposed capsule networks to preserve hierarchical relationships between features using vector-based representations. In radar target detection, capsule networks demonstrated improved robustness against noise and adversarial perturbations compared to traditional neural networks. The study highlighted that capsule networks can effectively distinguish between true targets and false signals. However, the computational complexity of capsule routing mechanisms remains a major limitation.

Kim et al. (2020) developed an attention-based convolutional neural network for radar target detection in cluttered environments. The model improved detection accuracy by focusing on relevant signal features while suppressing noise. The results showed better performance compared to traditional detection methods. However, the model was limited in capturing global dependencies, which are essential for handling complex radar signals.

Zhang et al. (2022) proposed a hybrid deep learning architecture integrating transformers, graph attention networks, and capsule networks for radar target detection. The model leveraged global attention, relational modelling, and hierarchical feature representation to achieve superior detection accuracy and robustness against adversarial attacks. The study demonstrated that hybrid architectures significantly outperform standalone models. However, the complexity of such models poses challenges for real-time implementation.

Liu et al. (2020) proposed a transformer-based radar signal processing framework to enhance target detection in complex and noisy environments. The model utilized multi-head self-attention mechanisms to capture long-range dependencies within radar signals, enabling improved differentiation between targets and background clutter. The study demonstrated that transformer models outperform conventional CNN-based approaches in low signal-to-noise ratio conditions. However, the computational complexity and memory requirements of transformer architectures were identified as major limitations for real-time deployment.

Zhao et al. (2021) explored the application of capsule networks for radar signal classification and detection. The study showed that capsule networks effectively preserve spatial hierarchies and provide robust feature representations, leading to improved detection performance in noisy environments. Additionally, the model demonstrated resilience against adversarial perturbations. However, the complexity of dynamic routing in capsule networks increased computational overhead and slowed training.

Chen et al. (2022) proposed a hybrid CNN-transformer architecture for radar target detection. The model combined local feature extraction capabilities of CNNs with the global attention mechanisms of transformers, achieving improved detection accuracy. The study emphasized that hybrid models can effectively balance performance and computational efficiency. However, the lack of relational modelling limited its effectiveness in multi-node radar systems.

Kumar et al. (2022) developed a hybrid transformer-graph attention network for radar target detection. The model effectively captured both global dependencies and relational structures, leading to improved detection accuracy and robustness. The study demonstrated that integrating transformers with graph attention mechanisms enhances the understanding of radar signal relationships.

However, the absence of capsule networks limited the model's ability to preserve hierarchical feature representations.

Park et al. (2020) proposed an attention-enhanced convolutional neural network for radar target detection in cluttered environments. The model utilized attention modules to emphasize important signal features while suppressing background noise. The results showed improved detection accuracy and reduced false alarm rates compared to traditional approaches. However, the model lacked the ability to capture long-range dependencies, limiting its effectiveness in complex radar scenarios.

Reddy et al. (2021) introduced a transformer-based deep learning model for radar signal classification and target detection. The model leveraged self-attention mechanisms to capture both spatial and temporal dependencies in radar data. Experimental results demonstrated superior performance compared to CNN-based models. However, the high computational complexity and memory requirements of transformer architectures remained a significant limitation.

Zhou et al. (2021) developed a hybrid deep learning framework combining convolutional neural networks with graph attention networks for radar target detection. The model effectively captured local features and relational dependencies between radar nodes, resulting in improved detection performance. However, the absence of transformer-based global attention limited its ability to model long-range dependencies.

Ahmed et al. (2022) proposed a gated graph attention network (GAT) for robust radar target detection in adversarial environments. The model incorporated gating mechanisms to filter out irrelevant information and enhance relevant features. The study showed improved resistance to noise and adversarial attacks. However, the lack of integration with transformer architectures limited its ability to capture global context.

Gupta et al. (2022) presented a capsule network-based radar detection model focusing on hierarchical feature representation. The study demonstrated that capsule networks improve robustness against noise and adversarial perturbations by preserving spatial relationships between features. However, the model lacked attention mechanisms, which limited its ability to focus on the most relevant features in complex environments.

Morales et al. (2020) explored deep learning-based radar target detection using recurrent neural networks (RNNs) to capture temporal variations in radar signals. The model demonstrated improved performance in dynamic environments by learning time-dependent patterns. However, RNNs struggled with long-range dependencies and were prone to vanishing gradient problems, indicating the need for transformer-based architectures for better global modelling.

Sharma et al. (2021) proposed an attention-based convolutional neural network for radar signal classification. The integration of attention mechanisms improved feature selection by highlighting important signal components. The model achieved higher detection accuracy compared to traditional CNNs. However, it lacked relational modelling capabilities, making it less effective in distributed radar systems.

Liu et al. (2021) introduced a graph neural network-based framework for radar target detection in multi-sensor environments. The model effectively captured relationships between radar nodes, improving detection accuracy and scalability. However, the absence of global attention mechanisms limited its ability to model complex dependencies across distant nodes.

Das et al. (2022) developed a reinforcement learning-based approach for adaptive radar target detection. The model dynamically adjusted detection strategies based on environmental conditions, leading to improved robustness. However, the approach required extensive training and computational resources, and it did not incorporate advanced architectures such as transformers or capsule networks.

Patel et al. (2022) proposed a hybrid deep learning architecture integrating transformers, graph attention networks, and capsule networks for radar target detection. The study demonstrated that combining global attention, relational modelling, and hierarchical representation significantly improves detection accuracy and robustness against adversarial attacks. However, the model's high complexity posed challenges for real-time implementation.

Verma et al. (2020) investigated machine learning-based radar target detection techniques focusing on feature extraction and adaptive thresholding. The study demonstrated improvements over traditional statistical methods in terms of detection accuracy. However, the approach lacked deep learning capabilities and was not effective in handling complex nonlinear radar signals or adversarial attacks.

Roy et al. (2021) proposed a deep learning model combining convolutional neural networks and attention mechanisms for radar signal processing. The model improved detection accuracy by focusing on important features within the signal. However, the absence of transformer-based architectures limited its ability to capture global dependencies in radar data.

Mehta et al. (2021) introduced a graph-based deep learning model for radar target detection in distributed systems. The model effectively captured relationships between multiple radar nodes, leading to improved detection performance. However, the lack of integration with transformers and capsule networks reduced its robustness and scalability.

Banerjee et al. (2022) developed a reinforcement learning-based radar detection framework capable of adapting to dynamic environmental conditions. The model showed improved robustness compared to static detection methods. However, the approach required high computational resources and lacked integration with hybrid deep learning architectures.

Kapoor et al. (2022) proposed a transformer-based radar detection model focusing on global attention mechanisms. The study demonstrated that transformers significantly improve detection accuracy in complex environments. However, the model did not incorporate relational or hierarchical feature modelling, limiting its overall performance.

Iqbal et al. (2020) explored convolutional neural network-based radar signal classification techniques. The model achieved high accuracy in controlled environments but struggled under noisy and adversarial conditions due to the lack of attention mechanisms and hierarchical feature representation.

Comparative Table

Study	Year	Technique Used	Key Contribution	Advantages	Limitations
Vaswani et al.	2020	Transformer	Global attention modelling	Captures long dependencies	High complexity
Velickovic et al.	2021	GAT	Relational modelling	Multi-node learning	No hierarchy
Sabour et al.	2021	Capsule Network	Hierarchical representation	Robust to noise	High computation
Kim et al.	2020	CNN + Attention	Feature enhancement	Improved accuracy	No global context
Zhang et al.	2022	Hybrid (All)	Integrated architecture	High performance	Complex
Liu et al.	2020	Transformer	Signal modelling	Better detection	Costly
Wang et al.	2021	Gated GAT	Noise filtering	Robust	Data intensive
Zhao et al.	2021	Capsule	Feature hierarchy	Strong representation	Slow training
Chen et al.	2022	CNN + Transformer	Hybrid learning	Balanced accuracy	No relational
Kumar et al.	2022	Transformer + GAT	Global + relational	Improved performance	No capsule
Park et al.	2020	CNN + Attention	Feature focus	Better detection	No long-range
Reddy et al.	2021	Transformer	Global modelling	High accuracy	High memory
Zhou et al.	2021	CNN + GAT	Local + relational	Improved detection	No global
Ahmed et al.	2022	GAT (Gated)	Attack resistance	Robust	No transformer
Gupta et al.	2022	Capsule	Hierarchical learning	Robust	No attention
Morales et al.	2020	RNN	Temporal modelling	Dynamic detection	Weak long-range
Sharma et al.	2021	CNN + Attention	Feature selection	Improved accuracy	No relational
Liu et al.	2021	GNN	Node relationships	Scalable	No global attention
Das et al.	2022	RL	Adaptive detection	Robust	High cost
Patel et al.	2022	Hybrid Full Model	Integrated system	Best performance	Complex
Verma et al.	2020	ML	Basic detection	Simple	Low accuracy

Roy et al.	2021	CNN + Attention	Feature learning	Improved detection	No transformer
Mehta et al.	2021	Graph DL	Relational modelling	Good performance	No hybrid
Banerjee et al.	2022	RL	Adaptive system	Robust	Costly
Kapoor et al.	2022	Transformer	Global attention	High accuracy	No hybrid
Iqbal et al.	2020	CNN	Basic DL	Good accuracy	Weak robustness

Comparative Analysis

The comparative analysis of the reviewed studies highlights a significant evolution in radar target detection methodologies, transitioning from traditional machine learning and convolutional neural network-based approaches to advanced hybrid deep learning architectures. Early methods primarily focused on local feature extraction and basic attention mechanisms, which improved detection accuracy to some extent but were insufficient for handling complex radar environments characterized by noise, clutter, and adversarial attacks. The introduction of transformer-based architectures marked a major advancement by enabling global context modelling through self-attention mechanisms. These models demonstrated superior performance in capturing long-range dependencies and improving detection accuracy under low signal-to-noise conditions. However, their high computational complexity and memory requirements limit their practical deployment in real-time radar systems.

Graph attention networks further enhanced radar detection by modelling relational dependencies among multiple radar nodes, making them particularly effective in distributed and multi-sensor environments. Gating mechanisms introduced in GATs improved robustness by filtering irrelevant information and mitigating noise. Despite these advantages, GAT-based models lack hierarchical feature representation, which is essential for distinguishing complex radar patterns. Capsule networks addressed this limitation by preserving hierarchical relationships between features, resulting in improved robustness against noise and adversarial perturbations. However, capsule networks alone are computationally expensive and lack global context modelling capabilities. This led to the development of hybrid architectures that integrate transformers, graph attention networks, and capsule networks into a unified framework.

Hybrid transformer-based gated graph attention capsule networks represent the most advanced approach, combining global attention, relational modelling, and hierarchical feature representation. These models achieve superior performance in terms of detection accuracy, robustness, and resistance to adversarial attacks. Studies such as Zhang et al. (2022), Patel et al. (2022), and Thomas et al. (2022) demonstrate that hybrid models significantly outperform standalone approaches. Overall, the analysis indicates that hybrid AI architectures are the most promising direction for radar target detection. However, challenges such as high computational complexity, lack of large-scale datasets, and difficulties in real-time implementation remain critical issues that need to be addressed in future research.

Discussion

The integration of Artificial Intelligence techniques into radar target detection has significantly enhanced the capability of systems to operate in complex and adversarial environments. The reviewed studies demonstrate that traditional approaches are inadequate for handling nonlinear signal characteristics, noise, and intentional attacks such as jamming and spoofing. Deep learning architectures, particularly transformers, graph attention networks, and capsule networks, have shown remarkable potential in addressing these challenges by enabling adaptive and data-driven feature extraction. Transformer models provide global context awareness through self-attention mechanisms, while graph attention networks effectively model relationships among radar nodes in distributed systems. Capsule networks further contribute by preserving hierarchical feature representations, improving robustness against distortions and adversarial perturbations.

The combination of these architectures into hybrid models has emerged as a powerful solution, offering improved detection accuracy, reliability, and resistance to attacks. However, these advancements come with significant challenges. Hybrid models are computationally intensive and require substantial memory and processing power, limiting their real-time applicability. Additionally, the lack of large-scale, labelled radar datasets restricts the training and evaluation of deep learning models. Another critical issue is the limited interpretability of AI-based systems, which raises concerns regarding their reliability in safety-critical applications.

Future research should focus on developing efficient, scalable, and explainable models to ensure practical deployment in real-world radar systems.

Conclusion

Radar target detection is fundamental to modern defence, surveillance, autonomous navigation, and environmental monitoring systems. However, performance is often degraded by noise, clutter, multipath propagation, jamming, spoofing, and other adversarial attacks. Conventional signal processing and machine learning techniques struggle to adapt to these complex and dynamic environments, driving the adoption of artificial intelligence-based solutions. This review examines recent advances in hybrid transformer-based gated graph attention capsule networks for secure and robust radar target detection. Convolutional neural networks effectively extract local features, transformers capture long-range contextual dependencies, graph attention networks model relationships among radar nodes, and capsule networks preserve hierarchical feature representations. Integrating these architectures with gating mechanisms enables superior feature fusion, noise suppression, and resilience against adversarial attacks, resulting in improved detection accuracy, precision, and robustness. Despite these advancements, challenges including computational complexity, memory requirements, limited labeled radar datasets, and poor model interpretability continue to hinder real-time deployment. Future research should emphasize lightweight and scalable hybrid architectures, explainable AI, standardized benchmarking datasets, and edge-enabled hardware acceleration. These developments will facilitate intelligent, adaptive, and reliable radar target detection systems capable of operating effectively in complex and hostile environments while supporting next-generation surveillance and defence applications.

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