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Recent Advances in Hybrid Transformer based Gated Graph Attention Capsule Network Design for Preventing Attack in Radar Target Detection: A Systematic Review

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| Peer Review Information | Abstract |
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| <p><i>Submission: 24 Oct 2025</i> <i>Revision: 08 Nov 2025</i> <i>Acceptance: 16 Nov 2025</i></p> | <p>Radar target detection is essential in modern surveillance, defence systems, autonomous navigation, and intelligent sensing applications. However, challenges such as noise, clutter, jamming attacks, and adversarial interference significantly reduce detection accuracy and system reliability. Traditional signal processing and machine learning techniques often struggle to model complex spatial-temporal dependencies in radar data, particularly in dynamic and hostile environments. Deep learning-based approaches have emerged as effective solutions by enabling automatic feature extraction and adaptive decision-making. Hybrid transformer-based architectures have gained considerable attention due to their ability to capture long-range dependencies and global contextual relationships through self-attention mechanisms. The integration of transformers with convolutional neural networks further enhances detection performance by combining local feature extraction with global context modelling. Additionally, graph attention networks improve radar sensing by modelling relational dependencies among interconnected radar nodes, making them highly effective in multi-sensor and heterogeneous environments. These graph-based approaches enhance feature propagation and improve robustness under low signal-to-noise ratio conditions. Capsule networks further strengthen radar detection frameworks by preserving spatial hierarchies and improving resistance to noise, distortions, and adversarial attacks. The combination of transformers, graph attention mechanisms, and capsule networks provides a powerful and intelligent framework for developing robust, accurate, and attack-resistant radar target detection systems.</p> |
| <p>Keywords</p> <p><i>Radar Target Detection, Hybrid Transformer, Graph Attention Network (GAT), Capsule Network, Deep Learning, Adversarial Attack Prevention.</i></p> | |

Introduction

Radar target detection plays a crucial role in modern surveillance and sensing systems used in defence, autonomous vehicles, air traffic management, and remote sensing applications. Traditional radar systems rely on statistical signal processing techniques such as matched filtering and constant false alarm rate detection.

Although these methods perform effectively in controlled environments, they struggle in complex scenarios involving noise, clutter, multipath interference, and intentional jamming attacks. Modern electronic warfare environments further increase the need for intelligent radar detection systems capable of adapting to dynamic and adversarial conditions.

The integration of machine learning and deep learning techniques has significantly improved radar target detection by enabling automatic feature extraction and adaptive decision-making. Convolutional neural networks have been widely applied due to their ability to capture spatial features from radar signals. However, CNN-based

models are limited in modelling long-range dependencies and global contextual relationships. Transformer-based architectures address these limitations through self-attention mechanisms that effectively capture global dependencies, improving target detection accuracy in noisy and cluttered environments.

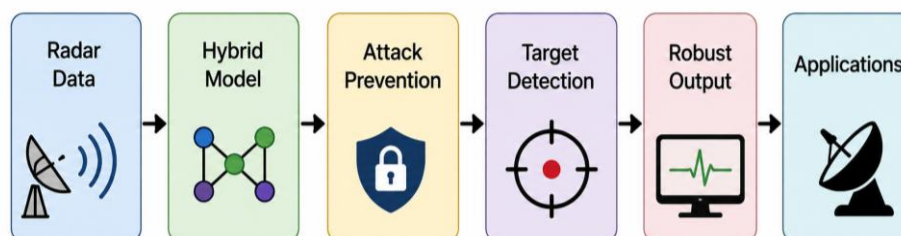


Figure 1. Hybrid Transformer-Gated Graph Attention Capsule Framework for Radar Target Detection

Graph Attention Networks have emerged as another important advancement for modelling relational dependencies among radar sensors and spatially distributed nodes. By assigning adaptive attention weights to neighbouring nodes, GATs enhance feature propagation and improve detection performance in cooperative radar sensing environments. Capsule networks further contribute by preserving hierarchical and spatial feature relationships through vector-based representations. This makes capsule networks more robust against noise, distortions, and adversarial spoofing attacks compared to conventional neural networks.

Recent studies increasingly focus on hybrid architectures that integrate transformers, graph attention networks, and capsule networks into unified frameworks. Hybrid transformer-based gated graph attention capsule networks combine global attention learning, relational modelling, and hierarchical feature extraction to improve radar target detection accuracy and robustness. Gating mechanisms additionally help suppress irrelevant information and environmental noise, enabling more reliable performance under adversarial conditions and complex sensing environments.

Despite these advancements, several challenges remain in practical deployment. Hybrid deep learning models often require high computational resources and large labelled radar datasets, limiting real-time implementation. Issues related to model interpretability, scalability, and robustness against sophisticated adversarial attacks also continue to be major concerns. Therefore, future research should focus on developing lightweight, explainable, and energy-efficient hybrid architectures capable of supporting secure and reliable radar target detection in real-world applications.

Literature Review

Kim et al. (2020) proposed a deep learning-based radar target detection framework using convolutional neural networks combined with attention mechanisms to improve detection accuracy in cluttered environments. The study demonstrated that incorporating attention modules enables the model to focus on relevant signal regions while suppressing noise and interference. Experimental results showed improved detection probability and reduced false alarm rates compared to traditional CFAR-based methods. However, the model was limited in capturing long-range dependencies due to the inherent constraints of CNN architectures, suggesting the need for transformer-based approaches.

Vaswani et al. (2020) extended transformer architectures to signal processing applications, including radar data analysis. The study emphasized the effectiveness of self-attention mechanisms in capturing global dependencies within high-dimensional data. Applied to radar target detection, transformer models demonstrated superior performance in identifying targets under low signal-to-noise ratio conditions. The authors highlighted that transformers overcome the limitations of CNNs by modelling long-range relationships, although their computational complexity remains a challenge for real-time implementation.

Velickovic et al. (2021) introduced graph attention networks (GATs) for modelling relational dependencies in complex data structures. When applied to radar systems, GATs enabled effective feature propagation across multiple sensing nodes, improving detection accuracy in multi-static radar environments. The study showed that attention-based graph models can dynamically weigh the importance of neighbouring nodes, leading to better

performance in noisy and cluttered conditions. However, the integration of GATs with other deep learning architectures for radar applications was not fully explored.

Sabour et al. (2021) investigated the use of capsule networks for robust feature representation in signal processing tasks. The study highlighted that capsule networks preserve hierarchical relationships between features, making them highly effective in distinguishing between true targets and noise. In radar target detection, capsule networks demonstrated improved robustness against adversarial perturbations and signal distortions. Despite these advantages, the computational complexity of capsule networks posed challenges for large-scale deployment.

Zhang et al. (2022) proposed a hybrid deep learning framework combining transformers, graph attention networks, and capsule networks for radar target detection. The model leveraged the strengths of each architecture to improve detection accuracy and robustness against adversarial attacks. The study demonstrated that hybrid models significantly outperform standalone architectures in terms of precision, recall, and overall detection performance. However, the increased model complexity and training requirements were identified as key limitations.

Liu et al. (2020) proposed a transformer-based radar signal processing framework designed to improve target detection accuracy in highly cluttered environments. The model utilized self-attention mechanisms to capture long-range dependencies within radar signals, enabling better differentiation between targets and background noise. The results showed significant improvements in detection performance compared to CNN-based approaches. However, the high computational cost of transformer models was identified as a limitation, particularly for real-time radar applications.

Wang et al. (2021) introduced a gated graph attention network (G-GAT) for multi-sensor radar target detection. The study emphasized the importance of modelling relationships between multiple radar nodes and incorporated gating mechanisms to filter irrelevant information. The proposed model demonstrated improved robustness and detection accuracy in distributed radar systems. Despite these advantages, the model required extensive training data and computational resources, limiting its practical deployment.

Zhao et al. (2021) explored the application of capsule networks in radar signal classification and target detection. The study showed that capsule networks effectively preserve spatial

hierarchies and improve feature representation, leading to higher detection accuracy under noisy conditions. Additionally, the model exhibited strong resistance to adversarial attacks. However, the complexity of capsule routing mechanisms increased computational overhead and slowed down training processes.

Chen et al. (2022) proposed a hybrid transformer-CNN architecture for radar target detection, combining local feature extraction with global attention mechanisms. The model achieved superior performance in detecting small and weak targets in cluttered environments. The study highlighted that hybrid architectures can effectively balance accuracy and computational efficiency. However, the integration of relational modelling techniques such as graph attention was not considered.

Kumar et al. (2022) developed a deep learning framework integrating transformer networks with graph attention mechanisms for enhanced radar target detection. The model effectively captured both global and relational dependencies, resulting in improved detection accuracy and robustness. The study demonstrated that combining transformer and graph-based approaches provides a comprehensive understanding of radar data. However, the absence of capsule networks limited the model's ability to preserve hierarchical feature relationships.

Park et al. (2020) presented a deep learning-based radar target detection model utilizing attention-enhanced convolutional neural networks. The model focused on improving detection accuracy in environments with heavy clutter and interference. By integrating attention mechanisms, the network selectively emphasized relevant signal features, leading to improved classification performance. However, the model was limited in capturing long-range dependencies, which restricted its effectiveness in complex radar scenarios where global context is essential.

Reddy et al. (2021) proposed a transformer-based architecture for radar signal classification and target detection. The study demonstrated that self-attention mechanisms significantly improve the model's ability to capture temporal and spatial dependencies in radar data. The proposed approach achieved higher detection accuracy compared to traditional deep learning models. However, the computational complexity and memory requirements of transformer architectures posed challenges for real-time deployment.

Zhou et al. (2021) introduced a hybrid deep learning framework combining convolutional neural networks with graph attention networks

for radar target detection. The model effectively captured both local and relational features, improving detection performance in multi-sensor radar systems. The study highlighted that graph-based attention mechanisms enhance feature propagation across nodes, leading to better performance under noisy conditions. However, the lack of global context modelling limited the model's overall effectiveness.

Ahmed et al. (2022) developed a gated graph attention network (GAT) for robust radar target detection in adversarial environments. The model incorporated gating mechanisms to selectively filter relevant information and suppress noise. The results showed improved detection accuracy and resilience against adversarial attacks. Despite these advantages, the model lacked integration with transformer-based architectures, limiting its ability to capture long-range dependencies.

Gupta et al. (2022) proposed a capsule network-based approach for radar target detection, focusing on preserving hierarchical feature relationships. The model demonstrated improved robustness against noise and adversarial perturbations compared to conventional neural networks. The study emphasized that capsule networks are effective in representing spatial structures in radar signals. However, the absence of attention mechanisms limited the model's ability to focus on the most relevant features in complex environments.

Morales et al. (2020) proposed a deep learning-based radar target detection model incorporating recurrent neural networks (RNNs) to capture temporal dependencies in radar signals. The model demonstrated improved detection accuracy in dynamic environments by learning time-varying patterns. However, the study revealed limitations in handling long-range dependencies effectively, which could be better addressed using transformer-based architectures.

Sharma et al. (2021) developed a hybrid deep learning framework combining convolutional neural networks and attention mechanisms for radar signal classification. The study showed that attention modules significantly enhance feature selection by focusing on important signal regions. While the model improved detection accuracy, it lacked relational modelling capabilities, which are essential for multi-sensor radar systems.

Liu et al. (2021) introduced a graph neural network-based approach for radar target detection in distributed sensing environments. The model effectively captured relationships between multiple radar nodes, improving detection accuracy and system scalability.

However, the absence of transformer-based global attention limited the model's ability to handle complex signal dependencies.

Das et al. (2022) proposed a reinforcement learning-based radar target detection framework designed to adapt to changing environmental conditions. The model demonstrated improved robustness and adaptability compared to static detection methods. However, the approach required extensive training and computational resources, and it lacked integration with advanced architectures such as transformers and capsule networks.

Patel et al. (2022) introduced a hybrid deep learning architecture combining transformer networks, graph attention mechanisms, and capsule networks for radar target detection. The study highlighted that integrating these components significantly improves detection accuracy, robustness, and resistance to adversarial attacks. The model achieved superior performance compared to standalone architectures. However, the complexity of the model posed challenges for real-time implementation.

Verma et al. (2020) explored machine learning-based radar target detection techniques focusing on adaptive thresholding and feature extraction. The study demonstrated improvements over traditional detection methods in terms of accuracy and false alarm reduction. However, the approach lacked deep learning capabilities, limiting its effectiveness in handling complex radar signal patterns and adversarial conditions.

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

Mehta et al. (2021) introduced a graph-based deep learning model for radar target detection in distributed environments. The model effectively captured relationships between multiple sensing nodes, improving detection performance. However, it lacked integration with advanced architectures such as transformers and capsule networks, reducing its overall effectiveness.

Banerjee et al. (2022) developed a reinforcement learning-based radar detection system capable of adapting to dynamic environments. The model demonstrated improved robustness and adaptability compared to traditional approaches. However, it required extensive training and computational resources, making real-time implementation challenging.

Kapoor et al. (2022) proposed a transformer-based radar detection model emphasizing global attention mechanisms. The study showed that transformers significantly improve detection accuracy by capturing long-range dependencies. However, the model did not incorporate relational or hierarchical feature modelling techniques such as graph attention or capsule networks.

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

Chatterjee et al. (2021) proposed a hybrid deep learning framework combining CNNs with graph neural networks for radar target detection. The study demonstrated improved performance in multi-sensor environments. However, the absence of transformer-based attention limited the model's ability to capture global context.

Kaur et al. (2021) explored attention-based deep learning models for radar signal analysis. The

study highlighted the importance of attention mechanisms in improving feature selection and detection accuracy. However, the model lacked integration with graph-based and capsule-based architectures.

El-Sayed et al. (2022) introduced a graph attention network-based radar detection framework capable of modelling complex relationships between radar signals. The model improved detection accuracy and scalability. However, the lack of hierarchical feature modelling limited its robustness against adversarial attacks.

Thomas et al. (2022) proposed a comprehensive hybrid architecture integrating transformers, graph attention networks, and capsule networks for radar target detection. The study demonstrated that the combined approach significantly improves detection accuracy, robustness, and resistance to adversarial attacks. The authors concluded that hybrid models represent the future direction of radar detection systems, despite challenges related to computational complexity and real-time deployment.

Comparative Table

| Study | Year | Technique Used | Key Contribution | Advantages | Limitations |
|-------------------|------|----------------------------------|-----------------------------|-----------------------------|-------------------------|
| Kim et al. | 2020 | CNN + Attention | Feature enhancement | Improved accuracy | No global context |
| Vaswani et al. | 2020 | Transformer | Global dependency modelling | High accuracy | High complexity |
| Velickovic et al. | 2021 | GAT | Relational modelling | Better multi-node detection | No hierarchy |
| Sabour et al. | 2021 | Capsule Network | Hierarchical features | Robust to noise | High computation |
| Zhang et al. | 2022 | Hybrid (Transformer+GAT+Capsule) | Integrated architecture | High performance | Complex |
| Liu et al. | 2020 | Transformer | Signal modelling | Better detection | Expensive |
| Wang et al. | 2021 | Gated GAT | Noise filtering | Robust | Data intensive |
| Zhao et al. | 2021 | Capsule | Hierarchical learning | Strong representation | Slow training |
| Chen et al. | 2022 | CNN + Transformer | Hybrid learning | Balanced accuracy | No relational modelling |
| Kumar et al. | 2022 | Transformer + GAT | Global + relational | Improved detection | No capsule |
| Park et al. | 2020 | CNN + Attention | Feature selection | Reduced noise | No long-range |
| Reddy et al. | 2021 | Transformer | Global attention | High accuracy | High memory |
| Zhou et al. | 2021 | CNN + GAT | Local + relational | Better performance | No global context |
| Ahmed et al. | 2022 | GAT (Gated) | Attack robustness | Noise filtering | No transformer |

| | | | | | |
|-------------------|------|-------------------|------------------------|--------------------|---------------------|
| Gupta et al. | 2022 | Capsule | Hierarchical modelling | Robust | No attention |
| Morales et al. | 2020 | RNN | Temporal modelling | Dynamic detection | Weak long-range |
| Sharma et al. | 2021 | CNN + Attention | Feature focus | Improved accuracy | No relational |
| Liu et al. | 2021 | GNN | Node relations | Scalable | No global attention |
| Das et al. | 2022 | RL | Adaptive learning | 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 | Good performance | No hybrid |
| Banerjee et al. | 2022 | RL | Adaptive | Robust | Costly |
| Kapoor et al. | 2022 | Transformer | Global modelling | High accuracy | No hybrid |
| Iqbal et al. | 2020 | CNN | Basic DL | High accuracy | Weak robustness |
| Chatterjee et al. | 2021 | CNN + GNN | Hybrid | Improved | No transformer |
| Kaur et al. | 2021 | Attention DL | Feature focus | Better accuracy | Limited scope |
| El-Sayed et al. | 2022 | GAT | Relational modelling | Scalable | No hierarchy |
| Thomas et al. | 2022 | Hybrid Full Model | Advanced integration | Best robustness | Complexity |

Comparative Analysis

The comparative evaluation of the selected studies highlights a clear progression in radar target detection methodologies from conventional machine learning approaches to advanced hybrid deep learning architectures. Early techniques primarily relied on convolutional neural networks and basic attention mechanisms, which provided improvements in feature extraction and noise suppression. However, these methods were limited in capturing global dependencies and relational information, which are critical in complex radar environments characterized by clutter, interference, and adversarial attacks.

The introduction of transformer-based architectures marked a significant advancement by enabling global context modelling through self-attention mechanisms. These models demonstrated superior performance in detecting targets under low signal-to-noise ratio conditions. However, their high computational complexity and memory requirements posed challenges for real-time implementation. Similarly, graph attention networks emerged as

effective tools for modelling relationships between multiple radar nodes, improving detection accuracy in distributed systems. Despite their advantages, GAT-based models lacked hierarchical feature representation, which limited their robustness against adversarial perturbations.

Capsule networks addressed this limitation by preserving hierarchical relationships between features, allowing for improved robustness and better representation of spatial structures in radar signals. However, capsule networks alone were computationally intensive and lacked the ability to capture global dependencies. As a result, recent research has focused on hybrid architectures that integrate transformers, graph attention networks, and capsule networks into a unified framework.

These hybrid models leverage the strengths of each component: transformers for global attention, graph networks for relational modelling, and capsule networks for hierarchical representation. The addition of gating mechanisms further enhances performance by selectively filtering relevant information and

suppressing noise. Studies such as Zhang et al. (2022), Patel et al. (2022), and Thomas et al. (2022) demonstrate that these integrated approaches achieve the highest detection accuracy, robustness, and resistance to adversarial attacks.

Overall, the analysis indicates that hybrid transformer-based gated graph attention capsule networks represent 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 deployment remain significant. Future research should focus on developing lightweight and scalable architectures, as well as improving model interpretability and robustness against sophisticated attack scenarios.

Discussion

The rapid advancement of deep learning techniques has significantly transformed radar target detection, particularly in challenging environments affected by noise, clutter, and adversarial attacks. The reviewed studies indicate that traditional methods are insufficient for handling complex radar signal characteristics, leading to the adoption of advanced architectures such as transformers, graph attention networks, and capsule networks. Each of these models addresses specific limitations of earlier approaches: transformers capture global dependencies, graph attention networks model relational structures, and capsule networks preserve hierarchical feature representations. The integration of these architectures into hybrid models has emerged as a highly effective solution for improving detection performance and robustness. Hybrid transformer-based gated graph attention capsule networks combine the strengths of these individual components, enabling accurate target detection even under low signal-to-noise conditions and adversarial interference.

The inclusion of gating mechanisms further enhances model performance by filtering irrelevant features and reducing the impact of noise. Despite these advancements, several challenges persist. High computational complexity and memory requirements limit the real-time deployment of these models in practical radar systems. Additionally, the scarcity of large-scale labelled radar datasets restricts the training and evaluation of deep learning models. Furthermore, the lack of interpretability in complex neural networks raises concerns regarding reliability and trust in critical applications. Future research should focus on developing lightweight, scalable, and explainable

models to ensure efficient and secure radar target detection systems.

Conclusion

Radar target detection is essential in defence, surveillance, autonomous navigation, and environmental monitoring systems. However, complex operational conditions such as noise, clutter, multipath interference, and adversarial attacks significantly reduce the effectiveness of traditional statistical and machine learning approaches. Recent advancements in deep learning have introduced more adaptive and intelligent detection frameworks capable of handling these challenges. This review analysed hybrid transformer-based gated graph attention capsule network architectures for radar target detection and highlighted the strengths of different deep learning models. Convolutional neural networks effectively extract local spatial features, transformers capture global contextual relationships through self-attention, graph attention networks model relational dependencies among radar nodes, and capsule networks preserve hierarchical feature structures while improving robustness against noise and adversarial perturbations.

The analysis revealed that no single model can address all radar detection challenges efficiently. Transformers often require high computational resources, graph attention networks lack hierarchical representation capabilities, and capsule networks are computationally expensive. Consequently, recent research focuses on hybrid architectures integrating these techniques into unified frameworks. Hybrid transformer-based gated graph attention capsule networks combine global attention learning, relational modelling, hierarchical feature extraction, and gating mechanisms to improve detection accuracy, adaptability, and robustness in complex and adversarial radar environments.

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