Strategic Analysis of Artificial Intelligence Integration in Next-Generation Defense Radar Systems

Executive Summary

The defense radar domain is currently navigating a critical inflection point, transitioning from the established paradigm of adaptive signal processing toward fully autonomous, cognitive sensing architectures driven by Artificial Intelligence (AI). This shift is not merely an incremental enhancement of legacy systems but a fundamental re-architecture necessitated by an increasingly hostile and congested electromagnetic spectrum (EMS). As adversarial capabilities evolve—characterized by the proliferation of hypersonic glide vehicles (HGVs), low-observable (stealth) platforms, and massive swarms of unmanned aerial systems (UAS)—traditional radar systems reliant on static heuristics, pre-programmed logic, and human-in-the-loop decision-making are rapidly reaching their theoretical and operational performance ceilings.

The integration of AI—specifically Deep Learning (DL), Deep Reinforcement Learning (DRL), and Neuromorphic Computing—enables radar systems to close the perception-action cycle. This capability allows sensors to perceive their environment, learn from temporal interactions, and optimize resources in real-time without operator intervention. The operational implications are profound: radars can now autonomously design waveforms to defeat specific jamming techniques, distinguish between biological clutter and micro-drones with high fidelity, and predict the trajectories of maneuvering hypersonic threats that defy standard kinematic models.

This report provides an exhaustive analysis of AI applications in defense radars, traversing the entire signal processing chain from the physical layer of waveform generation to the high-level semantic reasoning of battle management. It examines the emergence of Cognitive Radar (CR) architectures and the specific algorithmic implementations of Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) for Automatic Target Recognition (ATR). Furthermore, it analyzes the hardware foundations enabling these algorithms, contrasting the deterministic latency of Field Programmable Gate Arrays (FPGAs) with the extreme energy efficiency of emerging spiking neural networks (SNNs). Finally, the report reviews the operational deployment of these technologies in major defense programs, including the U.S. Army's TITAN and Sentinel, Raytheon's GhostEye, and Thales' Ground Master series, assessing how AI is reshaping the concepts of Joint All-Domain Command and Control (JADC2) and Mosaic Warfare.

1. The Operational Imperative: Why AI for Radar?

The impetus for integrating Artificial Intelligence into radar systems stems from three converging operational challenges that legacy systems can no longer address effectively: spectral congestion, hyper-maneuvering threats, and data saturation.

1.1 The Spectral Congestion Challenge

The electromagnetic spectrum is a finite resource that is becoming increasingly crowded. The proliferation of 5G and future 6G commercial communications networks, along with the ubiquity of wireless devices, has encroached upon bands traditionally reserved for radar operations. Simultaneously, the rise of Electronic Warfare (EW) means that adversaries are actively contesting the spectrum with intelligent jamming. Traditional radars, which operate on fixed frequencies or use predictable hopping patterns, are vulnerable to modern Digital Radio Frequency Memory (DRFM) jammers. AI enables **Cognitive Radar**, which can sense the spectral environment and dynamically adapt its transmission parameters—frequency, waveform, and pulse repetition frequency (PRF)—to find "white space" in the spectrum or to design waveforms that are orthogonal to jamming signals.

1.2 The Hyper-Maneuvering Threat

Legacy tracking algorithms, such as the Kalman Filter and the Interacting Multiple Model (IMM) filter, rely on predefined kinematic models (e.g., constant velocity, constant turn rate). Hypersonic Glide Vehicles (HGVs) and advanced cruise missiles exhibit highly non-linear dynamics, capable of pulling high-G maneuvers that violate the assumptions of these standard models. This leads to track loss or unacceptably large error ellipses. AI, particularly Physics-Informed Neural Networks (PINNs) and Transformer architectures, allows for the learning of complex, non-linear trajectories from vast datasets, offering a capability to predict future states of targets that legacy mathematics cannot model accurately.

1.3 Data Saturation and Cognitive Overload

Modern Active Electronically Scanned Array (AESA) radars, such as the AN/TPY-2 or the new LTAMDS, generate gigabytes of data per second. In a saturation attack involving drone swarms or salvo-fired missiles, the volume of tracks exceeds the cognitive capacity of human operators and the computational resources of standard rule-based schedulers. AI algorithms, specifically in the realm of Resource Management (RRM), provide the ability to prioritize thousands of tasks autonomously, ensuring that the radar focuses its energy on the most lethal threats while maintaining situational awareness.

2. Theoretical Foundations: The Cognitive Radar Paradigm

The evolution of radar technology is currently characterized by the move toward "Cognitive Radar" (CR). Unlike adaptive radar, which reacts to environmental changes based on fixed rules (e.g., "if rain clutter is detected, switch to circular polarization"), a cognitive radar interacts with the environment in a continuous feedback loop—the perception-action cycle—learning from experience to optimize its performance.

2.1 The Perception-Action Cycle

The core differentiator of cognitive radar is its ability to "sense, learn, and adapt." In this architecture, the transmitter and receiver are not isolated components but are coupled through a feedback channel. The receiver analyzes the radar return, assesses the quality of information—measured by metrics such as Signal-to-Interference-plus-Noise Ratio (SINR) or

Mutual Information (MI)—and informs the transmitter to adjust parameters for the next illumination.
This cycle mimics biological cognitive processes. The radar system utilizes **memory** (historical data on clutter maps and target behaviors) and **attention** (prioritizing sectors or targets) to manage its computational and energetic resources. For instance, if a radar detects a target in a high-clutter environment, the cognitive cycle allows it to autonomously switch waveforms or modulation schemes to maximize detection probability, a process that would be too slow for manual operator intervention.

2.2 Metacognitive Radar Architectures

To ensure robustness, advanced cognitive architectures employ a **Metacognitive Radar (MCR)** model. This hierarchical structure consists of:

- **MCR Knowledge:** Defines the learning rates and capabilities of various cognitive techniques.
- **MCR Monitoring:** continuously observes the performance of the radar's active strategy against the real-time Electromagnetic Environment (EME).
- **MCR Control:** regulates the learning process.

If the MCR monitor detects that the current Reinforcement Learning (RL) policy is underperforming—perhaps due to a sudden shift in the adversary's jamming strategy—the MCR controller intervenes, switching to a different learning strategy or reverting to a robust fallback mode. This meta-level management is crucial for preventing the "brittleness" often associated with AI systems when they encounter novel scenarios outside their training distribution.

3. Intelligent Signal Processing: The Physical Layer

At the physical layer, AI is revolutionizing how radar signals are processed to extract signals from noise, suppress clutter, and mitigate interference.

3.1 Deep Learning for Clutter Suppression

Sea and ground clutter present significant challenges for detecting small, slow-moving targets. Traditional Constant False Alarm Rate (CFAR) detectors utilize statistical models (e.g., Rayleigh, Weibull, K-distribution) to estimate the noise floor. However, these models often fail in heterogeneous environments where clutter is spiky or non-Gaussian.
Graph Neural Networks (GNNs): Recent research has demonstrated the efficacy of GNNs for sea clutter suppression. In this approach, radar echo data is modeled as a graph, where nodes represent range cells and edges represent spatiotemporal correlations. The GNN can distinguish between the chaotic, semi-random dynamics of sea waves and the structured kinematics of a maritime target. By analyzing the topology of the graph, the network achieves higher Signal-to-Clutter ratios (SCR) than conventional Doppler processing, effectively "de-noising" the scene based on structural relationships rather than just amplitude.
Generative Adversarial Networks (GANs): GANs are being applied to "inpaint" or reconstruct clean radar signals from data corrupted by clutter or jamming. The generator network learns the probability distribution of a "clean" environment and attempts to produce a synthetic signal that removes the artifacts. The discriminator network ensures that the reconstructed signal adheres to the physics of a valid radar return. This method has shown particular promise in Ground

Penetrating Radar (GPR) and maritime surveillance, where it can remove complex clutter patterns that traditional filters cannot isolate.

3.2 Interference Mitigation and Spectrum Sharing

The mutual interference between defense radars and commercial communication systems (or other radars) is a growing problem. AI offers robust solutions for interference mitigation that surpass traditional "blanking" or thresholding techniques.
Autoencoder Architectures: Deep Autoencoders are trained to compress the radar signal into a lower-dimensional latent space and then reconstruct it. By training the network on clean signals, the autoencoder learns the essential features of a valid target return. When presented with an interference-corrupted signal, the network reconstructs the "clean" version, effectively filtering out the interference which does not fit the learned latent features. This non-linear denoising capability preserves the phase information of the signal, which is critical for subsequent Doppler processing.
U-Net CNNs: Originally developed for biomedical image segmentation, U-Net architectures are applied to Range-Doppler maps. The network treats the interference as an image artifact (e.g., a "streak" or "blur" caused by an asynchronous pulse). The U-Net segments the interference and removes it, restoring the underlying target signature. This approach has proven superior to classical methods in preserving the integrity of weak targets that might otherwise be discarded along with the interference.

Table 1: Comparison of AI Architectures for Radar Interference Mitigation

Architecture	Mechanism	Key Advantage	Application Context
Deep Autoencoders	Latent space compression & reconstruction	Preserves phase information; Unsupervised learning capability	Automotive & Defense Mutual Interference
U-Net CNN	Image-to-image translation on Range-Doppler maps	High fidelity restoration of target signature	Dense spectral environments
Generative Adversarial Networks (GANs)	Adversarial generation of "clean" signal	Can reconstruct data lost to heavy jamming	Severe jamming/clutter scenarios
Recurrent Neural Networks (RNN/GRU)	Time-series prediction/filtering	effective for time-domain interference cancellation	Real-time stream processing

4. Automatic Target Recognition (ATR) and Classification

Automatic Target Recognition (ATR) represents the most mature application of AI in radar, shifting the discipline from template-based matching to feature-learning via Deep Neural Networks (DNNs).

4.1 Micro-Doppler Signature Classification

Micro-Doppler (m-D) refers to the secondary frequency modulations induced by the mechanical vibrations or rotations of a target's components—such as the propellers of a drone, the flapping wings of a bird, or the swinging limbs of a walking human. These signatures provide a unique fingerprint that allows radars to distinguish between targets that may have identical bulk velocities and Radar Cross Sections (RCS).

Drones vs. Birds: A critical requirement for modern short-range air defense (SHORAD) is distinguishing Unmanned Aerial Vehicles (UAVs) from biological clutter. Deep Convolutional Neural Networks (DCNNs) applied to Time-Frequency spectrograms have demonstrated superior performance in this classification task. The DCNN learns to identify the specific micro-Doppler patterns—such as the periodicity of wing beats versus the constant high-frequency modulation of rotor blades. Research indicates that fusing standard spectrograms with "edge-enhanced" micro-Doppler images (processed via phase stretch transforms) significantly boosts classification accuracy, reducing false alarm rates in complex urban environments.

4.2 High-Resolution Range Profile (HRRP) Recognition

High-Resolution Range Profiles (HRRP) provide a one-dimensional "image" of the target's scattering centers along the range dimension. A major challenge in HRRP recognition is **aspect sensitivity**; a target's profile changes drastically with even a small rotation, making template matching difficult.

Sequence Modeling with RNNs: Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks address this by treating the sequence of HRRPs over time as a time-series problem. The network learns the temporal evolution of the scatterers as the target moves, integrating information over multiple pulses to build a robust classification decision.

Graph Neural Networks (HRRPGraphNet): A novel approach involves transforming HRRP data into a graph structure. In this model, nodes represent the amplitude of range cells, while edges represent the spatial adjacency. The **HRRPGraphNet** architecture applies graph convolutions to extract global topological features of the target structure. This graph-based representation is inherently more robust to small aspect changes and deformations than standard vector-based inputs, allowing for high-accuracy recognition even with limited training data.

4.3 Synthetic Aperture Radar (SAR) and MLOps

In the domain of Synthetic Aperture Radar (SAR), AI is automating the analysis of imagery for Intelligence, Surveillance, and Reconnaissance (ISR). **Lockheed Martin** has demonstrated an AI-powered SAR ATR capability that autonomously detects and classifies maritime vessels. A key innovation in this program is the implementation of **Machine Learning Operations (MLOps)**. This framework allows for the rapid retraining and deployment of neural network models to the tactical edge. As new threat classes emerge (e.g., a new type of enemy corvette), the AI model can be updated centrally and pushed to deployed radar systems in near real-time, ensuring the ATR capability remains current.

5. Cognitive Radar Resource Management (RRM)

Modern Multifunction Radars (MFRs), particularly phased arrays, must simultaneously perform search, track, fire control, and communications. Allocating finite resources—time budget, energy budget, and computational cycles—among these competing tasks is an NP-hard optimization problem.

5.1 Reinforcement Learning for Beam Scheduling

Traditional RRM relies on heuristic schedulers (e.g., "earliest deadline first" or "highest threat first"). These static rules are brittle and often fail in dynamic saturation scenarios. **Deep Reinforcement Learning (DRL)** has emerged as a superior alternative.

In a DRL framework, the radar is the "agent," the battlefield is the "environment," and the scheduling decision is the "action." The agent receives a "reward" based on the successful tracking of high-priority targets and the maintenance of search volume coverage. Through training in high-fidelity simulations, the agent learns complex, non-intuitive strategies. For example, a DRL agent can learn to **interleave** radar pulses—utilizing the "dead time" between the transmission and reception of a long-range pulse to transmit short-range pulses for a different task. This capability maximizes the duty cycle and array utilization far beyond what human-designed heuristics can achieve.

Modified Q-Learning (MQL): Specific implementations like MQL use a Deep Q-Network (DQN) to prioritize tasks based on multi-dimensional criteria including target lethality, maneuver capability, and Quality of Service (QoS) constraints. Simulation results indicate that MQL-based schedulers consistently outperform adaptive heuristics in maintaining track completeness during saturation attacks.

5.2 Power Allocation and Low Probability of Intercept (LPI)

AI algorithms are also optimizing power allocation to enhance survivability. In **Distributed MIMO (D-MIMO)** radar networks, the objective is to track targets with sufficient accuracy (minimizing the Cramér-Rao Lower Bound) while emitting the minimum necessary power to avoid detection by enemy Electronic Support Measures (ESM).

Joint Antenna Scheduling and Power Allocation (JASPA): This scheme utilizes AI-driven non-convex optimization to predict the tracking error for various power levels. By dynamically allocating power only to the specific antenna elements and directions required for the current target state, the system minimizes its overall electromagnetic signature. Coalition game-theoretic approaches further enhance this by allowing autonomous radar nodes to form "coalitions" that cooperate to track a target, sharing the power burden and optimizing the trade-off between detection probability and LPI.

6. Tracking the Untrackable: Hypersonics and Maneuvering Targets

The tracking of Hypersonic Glide Vehicles (HGVs) represents one of the most severe challenges for modern radar. HGVs travel at speeds exceeding Mach 5 and, unlike ballistic missiles, execute unpredictable maneuvers within the atmosphere, rendering standard Keplerian and kinematic models obsolete.

6.1 Limitations of Legacy Filters

Standard filters like the **Interacting Multiple Model (IMM)** rely on a bank of predefined models (e.g., Constant Velocity, Constant Acceleration, Coordinated Turn). The filter switches between these models based on the target's behavior. However, the maneuvering envelope of an HGV is so complex that it often falls "between" the models, leading to model mismatch, lag, and eventually track loss. Similarly, standard data-driven approaches like basic LSTMs suffer from **cumulative error**, where small inaccuracies in prediction compound over time, leading to large divergence in long-term trajectory forecasting.

6.2 Physics-Informed Transformers (PIT)

To address these limitations, researchers have developed the **Physics-Informed Transformer (PIT)**. This architecture combines the sequence-modeling power of the Transformer (using self-attention mechanisms) with the governing laws of physics.
The PIT model incorporates three critical innovations:

1. **Top-\tau-mean Attention Mechanism:** This allows the network to focus on the most relevant historical data points to extract long-range dependencies in the trajectory, crucial for understanding the HGV's energy management profile.
2. **Generative Decoder:** Unlike standard regression outputs, the generative decoder is designed to predict future states in a way that minimizes error propagation over long horizons.
3. **Physical Knowledge Integration:** Most importantly, the kinematic equations of motion (incorporating gravity, drag, and lift vectors) are embedded into the network's loss function. This acts as a regularizer, penalizing the network if it predicts a trajectory that violates the laws of physics. This ensures that the AI's predictions are always physically plausible, significantly improving tracking accuracy and robustness even when radar data is intermittent or noisy.

Table 2: Comparison of HGV Tracking Approaches

Approach	Methodology	Strengths	Weaknesses
Interacting Multiple Model (IMM)	Probabilistic switching between fixed kinematic models	Established, interpretable	Fails when target dynamics exceed model definitions
Long Short-Term Memory (LSTM)	Recurrent Neural Network learning temporal patterns	Handles non-linear data better than IMM	Suffers from cumulative error propagation; slow training
Physics-Informed Transformer (PIT)	Self-attention mechanism constrained by physical laws	Long-range dependency extraction; Physical plausibility; High accuracy	High computational cost during training

7. Electronic Warfare and Cognitive ECCM

In the modern battlespace, radar and Electronic Warfare (EW) are inextricably linked. Cognitive Electronic Counter-Countermeasures (ECCM) use AI to defend the radar against sophisticated jamming attacks.

7.1 Jamming Recognition and Classification

The first step in ECCM is identifying the type of attack. CNNs are extensively used to classify jamming signals—such as spot jamming, barrage jamming, or Range Gate Pull-Off (RGPO)—by analyzing the Time-Frequency distribution (spectrogram) of the received signal. These "waterfall" plots serve as visual inputs to the CNN, which can classify jamming types with high accuracy even at low Jamming-to-Signal Ratios (JSR). This automated recognition triggers the appropriate counter-measure logic.

7.2 Game Theory and Adversarial Learning

The interaction between a radar and a jammer is effectively a zero-sum game. **Deep Reinforcement Learning (DRL)** agents are trained using game-theoretic frameworks (such as Stackelberg games or Markov games) to develop optimal anti-jamming strategies.
In this scenario, the radar (agent) observes the spectral state and selects an action (e.g., frequency hop, change PRF, null steering). The jammer (adversary) responds. The DRL agent learns a policy that maximizes the SINR over time. Advanced implementations utilize **Generative Adversarial Networks (GANs)** to simulate the jamming environment. One network acts as the radar trying to maintain detection, while the other acts as the jammer trying to disrupt it. This adversarial training regime forces the radar agent to develop robust, proactive strategies that can defeat even novel or adaptive jamming patterns that were not explicitly programmed into the system.

8. Hardware Architectures: Enabling AI at the Edge

The deployment of these sophisticated algorithms is constrained by the Size, Weight, and Power (SWaP) limitations of defense platforms. The choice of compute hardware is therefore critical.

8.1 Field Programmable Gate Arrays (FPGAs)

FPGAs remain the industry standard for radar signal processing due to their deterministic latency and parallel processing capabilities. Modern System-on-Chip (SoC) FPGAs, such as the **AMD Xilinx RFSoC**, integrate high-speed Analog-to-Digital Converters (ADCs) and Digital-to-Analog Converters (DACs) directly onto the same die as the programmable logic and ARM processors.
This integration is a key enabler for **Edge AI**. Inference engines (e.g., jamming detection CNNs) can be instantiated directly in the FPGA fabric close to the RF front end. This allows the radar to react to a threat in microseconds—orders of magnitude faster than if the data had to be sent to a central GPU or mission computer. This low latency is essential for real-time cognitive cycles, such as pulse-to-pulse waveform adaptation.

8.2 Neuromorphic Computing: The Low-Power Revolution

A disruptive technology emerging in radar hardware is **Neuromorphic Computing**, which utilizes Spiking Neural Networks (SNNs). Unlike standard Artifical Neural Networks (ANNs) that process continuous numerical values, SNNs operate on discrete "spikes" or events, mimicking the energy-efficient operation of biological brains.
IMEC, a leading semiconductor research hub, has developed the world's first SNN-based radar chip. Its performance metrics represent a paradigm shift:

- **Power Consumption:** It consumes **100 times less power** than traditional implementations.
- **Efficiency:** It can classify micro-Doppler signatures (e.g., distinguishing a drone from a bird) using only **30 μW** of power.
- **Latency:** It offers a tenfold reduction in latency compared to standard digital implementations.

This technology is particularly critical for "expendable" or highly constrained platforms, such as micro-UAS, loitering munitions, or battery-powered remote sentries. The low power draw allows for "always-on" sensing capabilities that would otherwise drain the battery of a conventional system.

BrainChip is another major player, partnering with the U.S. Air Force Research Laboratory (AFRL) to apply its **Akida** neuromorphic processor to radar signal processing. The Akida architecture processes data in an event-based manner, firing neurons only when relevant changes in the sensor data occur (sparsity). This event-driven processing is ideally suited for radar monitoring tasks where the scene is mostly static until a target appears.

9. Operational Architectures: JADC2 and Mosaic Warfare

AI-enabled radar is a foundational component of broader U.S. Department of Defense operational concepts: **Joint All-Domain Command and Control (JADC2)** and **Mosaic Warfare**.

9.1 JADC2 and AI-Driven Sensor Fusion

JADC2 envisions a unified network where any sensor can provide data to any shooter, regardless of service branch. AI provides the "Make Sense" capability within this architecture. A single radar track is often insufficient for a firing solution. AI-driven **Sensor Fusion** algorithms correlate data from disparate sources—a Navy AEGIS radar, an Air Force F-35 sensor, and a Space Force satellite—to create a single, high-fidelity "Golden Track."

This fusion occurs not just at the track level, but increasingly at the raw data level. AI algorithms can ingest raw I/Q data from multiple sensors to perform detection and classification that no single sensor could achieve alone. This capability significantly accelerates the OODA (Observe-Orient-Decide-Act) loop, automating the "Decide" phase by recommending the optimal effector (missile, jammer, or cyber payload) to the commander.

9.2 Mosaic Warfare and Distributed Autonomy

DARPA's **Mosaic Warfare** concept moves away from monolithic, expensive platforms (like a single massive radar ship) toward a "mosaic" of numerous low-cost, disaggregated sensors. In this architecture, AI is essential for **distributed resource management**.

If a dedicated radar node in the mosaic is jammed or destroyed, the AI network automatically reconfigures the remaining nodes to cover the blind spot. This "self-healing" capability relies on distributed AI agents negotiating coverage responsibilities in real-time, ensuring system resilience. A specific application is the use of AI to decompose a complex kill chain into dynamic services; if the primary tracking radar is lost, the AI can task a nearby drone swarm to form a coherent synthetic aperture to maintain the track.

10. Programmatic Landscape and Case Studies

The integration of AI into radar is not theoretical; it is actively shaping current programs of record across the global defense industry.

10.1 U.S. Army: TITAN and Sentinel

- **TITAN (Tactical Intelligence Targeting Access Node):** TITAN is the U.S. Army's next-generation ground station, designed to connect sensors from space, high-altitude, and aerial layers. **Palantir** and **Northrop Grumman** are developing the AI/ML backbone for TITAN, which ingests massive volumes of radar and optical data to provide automated targeting solutions for long-range precision fires. The system leverages AI to filter through clutter and identify high-value targets in seconds.
- **Sentinel Radar:** The Sentinel A4 program is incorporating AI to enhance its protection against cruise missiles and UAS, utilizing updated signal processing to handle the complex, low-altitude clutter environments where these threats operate.

10.2 Raytheon (RTX): GhostEye and LTAMDS

- **LTAMDS / GhostEye:** The Lower Tier Air and Missile Defense Sensor (LTAMDS) and its medium-range export variant, **GhostEye MR**, represent the cutting edge of AESA technology using Gallium Nitride (GaN). While the hardware provides 360-degree coverage and high power, Raytheon explicitly cites the integration of **"AI/ML decision aids"** to support operators. These aids likely assist in clutter mitigation and target classification, helping operators distinguish valid threats in complex environments. Furthermore, Raytheon utilizes AI in its modeling and simulation environment to predict radar performance and optimize designs before hardware fabrication.

10.3 Thales: Ground Master 400 Alpha

- **GM400α:** Thales has launched the **Ground Master 400 Alpha**, a long-range 3D surveillance radar that explicitly markets "advanced artificial intelligence capabilities." The system boasts **5x more processing power** than its predecessor, which is dedicated to running AI algorithms. These algorithms manage the massive data stream from the radar's digital stacked beams, enabling a 10% increase in instrumented range (up to 515km) and significantly improved classification of low-altitude, low-speed threats like UAVs, which are often lost in ground clutter by older systems.

10.4 Leonardo: Kronos Grand Mobile High Power

- **Kronos GM HP:** This active AESA radar, part of the SAMP/T NG air defense system, utilizes advanced signal processing to track tactical ballistic missiles and air-breathing threats. While explicit "AI" marketing is subtler than Thales, the system's ability to autonomously manage counter-countermeasures and prioritize hundreds of tracks implies a high degree of cognitive automation in its resource management logic.

11. Conclusion

The integration of Artificial Intelligence into defense radars represents a defining technological shift for the 21st-century military. We are witnessing the end of the era of **Adaptive Radar**—systems that were smart but static—and the dawn of **Cognitive Radar**—systems that learn, evolve, and reason.
This transition is driven by necessity: the human operator can no longer manage the speed of hypersonic warfare or the complexity of a congested spectrum. AI addresses these challenges by:

1. **Closing the Perception-Action Loop:** Enabling radars to adapt waveforms and schedules in real-time.
2. **Enhancing Physical Layer Processing:** Using GNNs and GANs to see through clutter and jamming that blinds legacy sensors.
3. **Enabling New Hardware:** Leveraging neuromorphic chips to bring supercomputer-class inference to expendable edge platforms.
4. **Facilitating Operational Concepts:** Acting as the enabling technology for JADC2 and Mosaic Warfare by automating the fusion and management of distributed sensor networks.

As these technologies mature, the measure of a radar's superiority will shift from purely physical attributes—power-aperture product—to the sophistication of the "digital brain" that controls it. The ability to update this brain via software (MLOps) will become as critical as the hardware itself, turning radar into a software-defined, intelligent asset capable of evolving faster than the threats it is designed to counter.

Works cited

1. Performance Analysis of Deep Learning Algorithms for Automotive Radar Interference Mitigation - Simple search - DiVA portal, http://bth.diva-portal.org/smash/record.jsf?pid=diva2:1735147 2. Spectrum Awareness - DeepSig, https://www.deepsig.ai/spectrum-awareness/ 3. Practical Aspects of Cognitive Radar - Institute for Information Sciences, https://www.ittc.ku.edu/~sdblunt/papers/IEEERC20_Cognitive.pdf 4. Deep Reinforcement Learning Control for Radar Detection and Tracking in Congested Spectral Environments - arXiv, https://arxiv.org/pdf/2006.13173 5. Hypersonic weapon interceptor developments - European Security & Defence, https://euro-sd.com/2025/09/articles/armament/46457/hypersonic-weapon-interceptor-developments/ 6. Long-Term Trajectory Prediction of Hypersonic Glide Vehicle Based on Physics-Informed Transformer | Request PDF - ResearchGate, https://www.researchgate.net/publication/374760130_Long-Term_Trajectory_Prediction_of_Hypersonic_Glide_Vehicle_Based_on_Physics-Informed_Transformer 7. [1805.07069] Multifunction Cognitive Radar Task Scheduling Using Monte Carlo Tree Search and Policy Networks - arXiv, https://arxiv.org/abs/1805.07069 8. Artificial intelligence meets radar resource management: A comprehensive background and literature review | IET Radar, Sonar & Navigation - IET Digital Library, https://digital-library.theiet.org/doi/full/10.1049/rsn2.12337 9. A machine learning approach to cognitive radar detection | Request PDF - ResearchGate, https://www.researchgate.net/publication/282931318_A_machine_learning_approach_to_cogniti

ve_radar_detection 10. Artificial Intelligence based Radar Technology: Current ..., https://www.researchgate.net/publication/395870869_Artificial_Intelligence_based_Radar_Technology_Current_Advancements_Future_Directions_and_Challenges 11. Reinforcement Learning based Waveform Design for Cognitive Imaging Radar, https://www.researchgate.net/publication/348988406_Reinforcement_Learning_based_Waveform_Design_for_Cognitive_Imaging_Radar 12. Radar Target Characterization and Deep Learning in Radar ... - MDPI, https://www.mdpi.com/2072-4292/15/15/3742 13. A Sea Clutter Suppression Method With Graph Neural Network for Maritime Target Detection, https://www.researchgate.net/publication/393351261_A_Sea_Clutter_Suppression_Method_with_Graph_Neural_Network_for_Maritime_Target_Detection 14. Mutual Interference Suppression and Signal Enhancement Method for Ground-Penetrating Radar Based on Deep Learning - MDPI, https://www.mdpi.com/2079-9292/13/23/4722 15. Maritime Clutter Suppression with Neural Networks - MATLAB & Simulink - MathWorks, https://www.mathworks.com/help/radar/ug/maritime-clutter-removal-with-neural-networks.html 16. A DNN Autoencoder for Automotive Radar Interference Mitigation - ResearchGate, https://www.researchgate.net/publication/352171316_A_DNN_Autoencoder_for_Automotive_Radar_Interference_Mitigation 17. A DNN Autoencoder for Automotive Radar Interference Mitigation - Semantic Scholar, https://www.semanticscholar.org/paper/A-DNN-Autoencoder-for-Automotive-Radar-Interference-Chen-Taghia/c0b5f2e531a14d388172fb4f0ee845d091f80f87 18. Fully Convolutional Neural Networks for Automotive Radar Interference Mitigation - arXiv, https://arxiv.org/pdf/2007.11102 19. Automatic target recognition - Wikipedia, https://en.wikipedia.org/wiki/Automatic_target_recognition 20. Micro-Doppler radar signatures for intelligent target recognition - DTIC, https://apps.dtic.mil/sti/tr/pdf/ADA427483.pdf 21. Micro-Motion Classification of Flying Bird and Rotor Drones via Data Augmentation and Modified Multi-Scale CNN - MDPI, https://www.mdpi.com/2072-4292/14/5/1107 22. Classification of drones and birds using convolutional neural networks applied to radar micro‐Doppler spectrogram images - Semantic Scholar, https://www.semanticscholar.org/paper/Classification-of-drones-and-birds-using-neural-to-Rahman-Robertson/36036208428d5ca9607842f66de630649f0a53f6 23. Classification of drones and birds using convolutional neural networks applied to radar micro-Doppler spectrogram images | Request PDF - ResearchGate, https://www.researchgate.net/publication/338145135_Classification_of_drones_and_birds_using_convolutional_neural_networks_applied_to_radar_micro-Doppler_spectrogram_images 24. HRRPGraphNet: A Graph Neural Network Based Approach for HRRP Radar Target Recognition - arXiv, https://arxiv.org/html/2407.08236v1 25. Lockheed Martin Revolutionizes Maritime Surveillance with AI-Powered Technology, https://news.lockheedmartin.com/2025-07-16-Lockheed-Martin-Revolutionizes-Maritime-Surveillance-with-AI-Powered-Technology 26. A Modified Reinforcement Q-Learning Method for Multi-function Phased Array Radar Beam Scheduling - IEEE Xplore, https://ieeexplore.ieee.org/iel7/10101484/10100740/10101623.pdf 27. Dynamic Adaptive Resource Scheduling for Phased Array Radar - arXiv, https://arxiv.org/pdf/2409.19201 28. Artificial Intelligence Meets Radar Resource Management Lit Review - Amos Hebb, https://amoshebb.com/blog/artificial-intelligence-meets-radar-resource-management-lit-review/ 29. Airborne Radar Anti-Jamming Waveform Design Based on Deep Reinforcement Learning - PMC - PubMed Central, https://pmc.ncbi.nlm.nih.gov/articles/PMC9692253/ 30. Joint Antenna Scheduling and Power Allocation for Multi-Target Tracking under Range Deception Jamming in Distributed MIMO Radar System - MDPI, https://www.mdpi.com/2072-4292/16/14/2616 31.

Coalition Game Theoretic Power Allocation Strategy for Multi-Target Detection in Distributed Radar Networks - MDPI, https://www.mdpi.com/2072-4292/15/15/3804 32. Monday, November 10, 2025, https://www.ifs.tohoku.ac.jp/icfd/2025/program/Precise2025.pdf 33. Long-Term Trajectory Prediction of Hypersonic Glide Vehicle Based ..., https://ieeexplore.ieee.org/document/10286284/ 34. Long-Term Trajectory Prediction of Hypersonic Glide Vehicle Based on Physics-Informed Transformer - IEEE Xplore, http://ieeexplore.ieee.org/document/10286284/ 35. Deep learning and recognition of radar jamming based on CNN - ResearchGate, https://www.researchgate.net/publication/341588011_Deep_learning_and_recognition_of_radar_jamming_based_on_CNN 36. Radar Jamming Recognition: Models, Methods, and Prospects - IEEE Xplore, https://ieeexplore.ieee.org/iel8/4609443/10766875/10816388.pdf 37. Game-theoretic Learning Anti-jamming Approaches in Wireless Networks - arXiv, https://arxiv.org/pdf/2207.00159 38. A Review of Game Theory Analysis in Cognitive Radar Anti-jamming - 电子与信息学报, https://jeit.ac.cn/en/article/doi/10.11999/JEIT200843 39. Sensing-Throughput Tradeoffs with Generative Adversarial Networks for NextG Spectrum Sharing - arXiv, https://arxiv.org/pdf/2212.13598 40. Beyond the GPU: The Strategic Role of FPGAs in the Next Wave of AI - arXiv, https://arxiv.org/html/2511.11614v1 41. HLS-Based FPGA Implementation of Multi-Label Learning for Radar Signal Recognition, https://ieeexplore.ieee.org/document/10390748/ 42. Radar and EW - AMD, https://www.amd.com/en/solutions/aerospace-and-defense/radar-and-ew.html 43. Imec Builds World's First Spiking Neural Network-Based Chip for ..., https://www.imec-int.com/en/articles/imec-builds-world-s-first-spiking-neural-network-based-chip-for-radar-signal-processing 44. BrainChip secures $1.8M AFRL contract to advance neuromorphic radar for edge military systems, https://www.edgeir.com/brainchip-secures-1-8m-afrl-contract-to-advance-neuromorphic-radar-for-edge-military-systems-20241211 45. BrainChip to improve radar signalling applications for US AFRL - Air Force Technology, https://www.airforce-technology.com/news/brainchip-radar-signalling-us-afrl/ 46. Joint Force Coordination for Full Scale Operations - Booz Allen, https://www.boozallen.com/insights/defense/c2-command-and-control/joint-force-coordination-for-full-scale-operations.html 47. The Future of Air Superiority: Command of the Air in High Intensity Warfare - Ifri, https://www.ifri.org/sites/default/files/2025-09/ifri_gorremans_future_air_superiority_2025.pdf 48. Virtual System of Systems Analysis of Advanced Technologies for Joint All Domain Command and Control (JADC2) - MODSIM World 2025, https://www.modsimworld.org/papers/2023/MODSIM_2023_paper_4853.pdf 49. Mosaic Warfare - Defense One, https://www.defenseone.com/insights/cards/how-ai-changing-way-warfighters-make-decisions-and-fight-battlefield/5/ 50. AlphaMosaic: An Artificially Intelligent Battle Management Architecture - Aerospace Research Central, https://arc.aiaa.org/doi/pdfplus/10.2514/1.I010991 51. Research, Development, Test & Evaluation, Army RDT&E − Volume III, Budget Activity 6 - Justification Book, https://www.asafm.army.mil/Portals/72/Documents/BudgetMaterial/2025/Base%20Budget/Research,%20Development,%20Test%20and%20Evaluation/RDTE%20-%20Vol%203%20-%20Budget%20Activity%206.pdf 52. Radio-as-a-Sensor Innovation: AI-Driven Battlefield Intelligence Transformation in 2025, https://debuglies.com/2025/09/20/radio-as-a-sensor-innovation-ai-driven-battlefield-intelligence-transformation-in-2025/ 53. Next Generation Over-the-Horizon Radar | Raytheon - RTX, https://www.rtx.com/raytheon/what-we-do/strategic-missile-defense/next-generation-over-the-horizon-radar 54. Visualizing the art of the possible | Raytheon - RTX, https://www.rtx.com/raytheon/news/2021/03/01/visualizing-art-possible 55. Ground Master 400 Alpha, taking long-range air surveillance to the next level | Thales Group, https://www.thalesgroup.com/en/news-centre/press-releases/ground-master-400-alpha-taking-long-range-air-surveillance-next-level 56. Thales launches GM400 Alpha long-range 3D surveillance radar - Airforce Technology, https://www.airforce-technology.com/news/thales-launches-gm400-alpha-radar/ 57. Ground Master 400 Alpha long-range 3D radar unveiled by Thales, https://militaryembedded.com/radar-ew/sensors/ground-master-400-alpha-long-range-3d-radar-unveiled-by-thales 58. Leonardo Completes SAMP/T NG Air Defense System Radar Acceptance Test, https://thedefensepost.com/2023/08/04/leonardo-samp-t-ng-radar/ 59. PAS 2023 - Leonardo's Kronos Grand Mobile HP boosts SAMP/T capabilities, https://www.edrmagazine.eu/leonardos-kronos-grand-mobile-hp-boosts-samp-t-capabilities