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ARIA: ADAPTIVE RADAR INTELLIGENCE ARCHITECTURE

A PROPOSED AI-AUGMENTED FRAMEWORK FOR NEXT-GENERATION RADAR SYSTEMS

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ABSTRACT

Some of the common operational challenges in modern radar systems are high false alarm rate (10-30% for clutter environments), detection-to-track latency of 0.5-3 seconds, blind zone of the radar system due to terrain (25-40% of monitored areas), and Electronic Counter Measures (ECM) ranging from spot jamming to Digital RF Memory (DRFM) spoofing [1, 2]. In this paper, we present the multi-static distributed sensor mesh networking, as well as the novel technologies of Convolutional Neural Network (CNN)-based target classification [7, 17] and Long Short-Term Memory (LSTM) predictive tracking [9, 15] and autonomous threat assessment [5, 20] and present ARIA — Adaptive Radar Intelligence Architecture, a novel software and hardware integration framework that unifies these five independently developed technologies.

The proposed hybrid framework includes a ResNet-like CNN with multi-head attention (MHA) [17] trained using SAR and Doppler radar data for target classification, LSTM trajectory prediction with a distributed mesh of 20–50 fixed sensor nodes for coverage redundancy [12] and interacting multiple model (IMM) hybrid integration for tracking [9, 15]. The results obtained from simulation-based evaluation against literature baselines give the proposed target classification accuracy of 85-92% under operational conditions, which is much higher than the CFAR baseline of 72-83% in an actual clutter environment [7, 8]. All performance values are unvalidated research hypothesis that needs to be validated in the field. The actual value of the framework is a shared architecture proposal that brings existing component technologies together in a coherent and deployable radar intelligence architecture.

KEYWORDS: Adaptive Radar Intelligence, CNN-based Target Classification, LSTM Predictive Tracking, Multi-Static Radar, ECCM, Frequency Hopping, Cognitive Radar, SAR, CFAR, Electronic Countermeasures, Distributed Sensor Mesh, Autonomous Threat Assessment, ResNet, Transformer, Domain Randomisation

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1. INTRODUCTION

1.1 Background and Motivation

Radar systems are the backbone of modern air defence, border surveillance and maritime domain awareness operations. These radar systems have changed a great deal over the years, since the first operational networks were used during the Second World War, in terms of range, resolution and complexity of the signal processing [1, 2]. But today, basic constraints from physics and from classical signal processing architectures still hinder the effectiveness of operations [1].

Modern radar, using Constant False Alarm Rate (CFAR) detection algorithms, have a false alarm rate of 10-30% at complex clutter environments, leading to operator alert fatigue and missing real threats [1]. Typical phased-array processing pipelines achieve detection to track latency of 0.5–3 s, depending on the waveform and processing configuration: At Mach 3 target velocities, the detection to track latency is about 1 km of target displacement per second [2]. With the use of single site radar installations, an estimated 25-40% of border terrain can be masked from surveillance, due to line-of-sight terrain masking.

With the advent of Artificial Intelligence and deep learning architectures, there is a promising opportunity to overcome these drawbacks [13, 16, 18]. In a SAR target classification task, the CNN has shown the accuracy of 72–98% [7, 8]. LSTM networks have been demonstrated to predict the target trajectory at > 0.5–1.5 seconds ahead of time [9, 15]. Many of the technologies have been proven independently, and they have not been suggested in an integrated architectural framework that is optimized for the integration with next-generation radar surveillance.

1.2 Problem Statement

Current radar systems architectures tackle partial operational challenges with ad hoc engineering solutions, but fail to offer system-level benefits [1, 4]. CFAR detectors have the effect of decreasing false alarms at the expense of sensitivity. The conventional ECCM implementations do not offer adaptive intelligence, just frequency agility [4, 10]. The classification of targets depends on the human operator judgment, and the error rate in the operational stress condition is 15-20% [5]. The lack of a common architecture that combines classification using AI augmentation, predictive tracking, distributed sensors, and AI-based countermeasures is the biggest gap ARIA aims to fill.

1.3 Research Objectives

The main aims of this research are: (i) to propose a unified software and hardware integration architecture (ARIA) that combines five independently researched radar intelligence technologies, into a coherent operational framework; (ii) to evaluate the theoretical improvements in target classification that could be obtained using CNN-based classification of multi-modal SAR and Doppler data [7, 8]; (iii) to assess the feasibility of LSTM-based predictive tracking with IMM hybrid integration [9]; (iv) to define a realistic deployment approach for the distributed sensor mesh to address terrain-masking limitations [12]; and (v) to identify critical research gaps that need to be resolved prior to the components of ARIA transitioning from lab prototype to field deployment.

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1.4 Scope and Original Contributions

This research brings the following original scientific contributions: (i) an innovative joint architectural framework (ARIA) outlining and specifying integration interfaces among CNN classification [17], LSTM tracking [15], multi-static sensing [12], ECCM [10] and autonomous threat assessment [20] components; (ii) an honest comparative analysis distinguishing between technologies that are currently in use in the operational domain and those in active research stage; (iii) a realistic performance hypothesis framework firmly based on literature baselines [7, 8, 9]; (iv) identification of four critical open research problems; and (v) a grounded development roadmap with milestone-based validation gates consistent with realistic research timelines.

2. LITERATURE REVIEW

2.1 CNN-Based SAR Target Classification

Data augmentation combined with Convolutional Neural Networks (CNNs) was shown by Ding et al. [7] to be able to recognize targets in the MSTAR dataset with 97–98% accuracy in a controlled laboratory environment with known target classes, thus proving the feasibility of deep learning for target recognition in the field of SAR. Huang et al. [8] proposed the OpenSARShip 2.0 dataset with real Sentinel-1 images to tackle the challenges of maritime target discrimination, and reported an accuracy of 91–94%, with notably higher accuracy variation compared to the MSTAR results. He et al. [17] introduced the ResNet architecture with residual connections, which paves the way for training very deep networks to serve as the backbone of the classification module in ARIA's Module 1. In practice, the accuracy of CNN radar classifiers has been evaluated in real clutter environments, ranging from 72% to 83%, and 45% to 60% for novel and unseen threat signatures, respectively [7, 8].

2.2 LSTM Predictive Tracking for Radar Applications

In radar-based trajectory prediction application, Schreiber et al. [9] demonstrated the ability of LSTM network to predict the position error of about 15–25 metres for a prediction horizon of 1 second. The LSTM architecture with gating mechanisms, which is the theoretical foundation behind ARIA's Module 2, was originally proposed by Hochreiter and Schmidhuber [15] for modeling long sequences. The Interacting Multiple Model-LSTM (IMM-LSTM) hybrid is the state-of-the-art solution in tracking maneuvering targets, but this approach has not yet been validated at operational radar update rates in 2024 [5, 9].

2.3 Multi-Static and Distributed Radar Networks

The concepts behind multi-static radar have already been successfully implemented in many operational military radars, such as the North Warning System (NORAD) and the Air Command and Control System (ACC) for NATO. India's IAF Air Defence network has distributed radar installations maintained by DRDO.DRDO is responsible for maintaining distributed radar installations that provide overlapping coverage for the IAF Air Defence network [6]. In its application for wide area surveillance, autonomous radar drone swarm networks have been studied by Niu et al. [12] who achieved lab prototype operation with 10–30 nodes. The addition of 500+ nodes to the drone-based radar swarm is a challenge that has

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not yet been resolved, such as battery endurance, spectrum deconfliction and IFF protocol integration [12].

2.4 Electronic Counter-Countermeasures

Agile frequency hopping for radar ECCM has been standard operational practice since the 1980s, deployed in systems including the AN/TPY-2 and S-400 families, providing effective resistance against spot jamming [4]. Haykin [10] proposed the cognitive radar paradigm implementing AI-driven real-time waveform adaptation using reinforcement learning [18]; however, cognitive radar ECCM remains at academic research stage with no known operational deployment as of 2024. Mnih et al. [18] established the Deep Q-Network (DQN) framework for reinforcement learning that underlies cognitive waveform adaptation approaches.

2.5 Explainability and Distributed Intelligence

Lundberg and Lee [20] proposed SHAP (SHapley Additive exPlanations), providing unified attribution-based model interpretability essential for safety-critical radar decision support. McMahan et al. [19] introduced Federated Learning, enabling privacy-preserving distributed model training across sensor nodes without centralizing raw radar data — directly applicable to distributed radar network intelligence. Goodfellow et al. [14] introduced Generative Adversarial Networks providing the theoretical basis for synthetic radar data generation addressing training data scarcity. Vaswani et al. [16] proposed the Transformer architecture with self-attention mechanisms, enabling superior sequential target modeling in ARIA's multi-target tracking module.

2.6 Research Gap Identification

The survey reveals four research gaps that motivate ARIA, as highlighted below: (i) no large-scale real-world datasets with labeled multi-mode radar data under operational conditions [7, 8] (ii) no proof-of-concept IMM-LSTM hybrid at operational radar update rates, with LSTM predictive tracking being inadequate for high-g maneuvering targets [9] (iii) no open-source distributed radar node coordination protocol for spectrum deconfliction and sub-microsecond time synchronization [12] (iv) CNN classifiers are vulnerable to adversarial DRFM spoofing attacks with only 5% modification [7, 24].

2.7 Comparative Positioning Against Related Integrated AI-Radar Systems

While Sections 2.1-2.5 reviewed the individual technologies underlying ARIA's five modules, it is equally important to distinguish ARIA from prior work that already combines multiple AI techniques within a single radar or sensing pipeline. Chen et al. [21] proposed a CNN-based micro-Doppler classifier for UAV discrimination, but the system addresses only the

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classification function in isolation, with no tracking, mesh sensing, or ECCM layer. Park et al. [22] developed a Transformer-based ISAR classifier for maritime targets, again limited to the classification stage. Li and Zhang [23] investigated reinforcement-learning-based waveform design and beam scheduling, a contribution restricted to the ECCM/adaptive-waveform function. Guo et al. [27] used Generative Adversarial Networks for SAR data augmentation to improve Automatic Target Recognition (ATR) performance, addressing data scarcity rather than system-level integration. Kim et al. [28] proposed an edge-AI architecture for real-time radar target detection in IoT-based distributed sensor networks, which is the closest prior work to ARIA's distributed-mesh module, but does not incorporate predictive tracking, cognitive ECCM, or threat-assessment layers. Wagner et al. [29] combined LSTM networks with attention mechanisms for multi-target tracking in dense environments, corresponding only to ARIA's Module 2 function. Rani et al. [30] applied Random Forest and SVM classifiers for weather-clutter suppression in airborne radar, a narrower detection-stage contribution.

Table 3B summarises this comparison against the seven closest single- or dual-function prior systems identified in the survey.

Reference	Technology Focus	Module(s) Addressed	Integration Scope
Chen et al. [21]	CNN micro-Doppler UAV classification	Module 1 only	Single-function
Park et al. [22]	Transformer ISAR maritime classification	Module 1 only	Single-function
Li & Zhang [23]	RL waveform design & beam scheduling	Module 4 only	Single-function
Guo et al. [27]	GAN-based SAR data augmentation	Pre-Module 1 (data pipeline)	Single-function
Kim et al. [28]	Edge AI, IoT distributed radar detection	Module 3 (partial)	Two-function
Wagner et al. [29]	LSTM + attention multi-target tracking	Module 2 only	Single-function
Rani et al. [30]	RF/SVM weather-clutter suppression	Pre-detection (clutter stage)	Single-function
ARIA (this work)	CNN + LSTM + Mesh + ECCM + XAI, unified	Modules 1-5	Five-function integrated

Table 3B: Comparative Positioning of ARIA Against Representative Single- and Dual-Function AI-Radar Systems [21, 22, 23, 27, 28, 29, 30]

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As shown in Table 3B, no prior work in the surveyed literature proposes a single architecture that jointly spans classification, predictive tracking, distributed sensing, cognitive ECCM, and explainable threat assessment; each address at most one or two of these functions in isolation. This distinction is the basis of ARIA's claimed novelty: not a new algorithm at the component level, but an explicit orchestration-layer specification unifying five previously disconnected research threads into one operational pipeline, together with the interface definitions and data-flow logic presented in Section 3.6.

3. PROPOSED METHODOLOGY AND SYSTEM ARCHITECTURE

Note on scope: ARIA is presented here as a conceptual architectural framework. No hardware prototype has been constructed and no field trial has been conducted at this stage; all performance figures presented in this and the following sections are literature-grounded research hypotheses requiring experimental validation, as detailed in Section 8.2.

The proposed ARIA framework adopts a modular five-component architecture establishing a hierarchical signal processing pipeline from physical radar sensing to autonomous threat assessment output. Each component addresses specific operational limitations identified in the preceding gap analysis, clearly distinguishing between components employing currently deployed technology and those requiring research validation before operational deployment.

3.1 Module 1 — CNN-Based Target Classification

The target classification module employs a ResNet-style Convolutional Neural Network [17] with multi-head attention mechanism [16] trained on multi-modal radar data combining Synthetic Aperture Radar imagery and Doppler velocity profiles. Training data combines MSTAR military vehicle SAR chips [7], OpenSARShip maritime target Sentinel-1 imagery [8], and synthetically augmented data employing domain randomization to improve generalization.

The CNN objective function with regularization is formulated as: $L(\theta) = -\Sigma_i\, y_i \log(\hat{y}_i) + \lambda\|\theta\|_2^2$ ... (1), where y_i represents the true target class label, $\hat{y}_i$ is the softmax classification output, θ denotes network parameters, and λ is the L2 regularization coefficient. The multi-head attention mechanism [16] computes cross-modal feature correlation as: $\text{Attention}(Q, K, V) = \text{softmax}(QK^T / \sqrt{d_k}) \cdot V$ ... (2), where Q, K, V represent Query, Key, Value matrices across SAR and Doppler feature spaces. The proposed target accuracy of 85–92% under operational conditions is a research hypothesis requiring field trial validation; current literature baseline is 72–83% in real clutter environments [7, 8].

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3.2 Module 2 — LSTM Predictive Tracking

The predictive tracking module implements a bidirectional LSTM network [15] with IMM hybrid integration. The LSTM gate equations are: $f^t = \sigma(Wf[h^t_{-1}, x^t] + bf)$; $i^t = \sigma(Wi[h^t_{-1}, x^t] + bi)$ ... (3); $\tilde{C}^t = \tanh(Wc[h^t_{-1}, x^t] + bc)$; $C^t = f^t \odot C^t_{-1} + i^t \odot \tilde{C}^t$ ... (4). The IMM hybrid integrates the LSTM predictor [9] with a classical Kalman filter bank [5] employing multiple motion models through probabilistic weighting, addressing the fundamental LSTM failure mode against high-G maneuvering targets.

3.3 Module 3 — Distributed Multi-Static Sensor Mesh

The distributed sensing module proposes deployment of 20–50 fixed ground-based radar sensor nodes in a multi-static mesh configuration for terrain-masking mitigation [3, 12]. This represents a significant downscaling from preliminary ARIA documentation claiming 500 drone-mounted nodes; current literature supports 10–30 node laboratory prototypes [12]. Track-to-track association employs the Joint Probabilistic Data Association (JPDA) algorithm across node contributions [5]. Time synchronization across nodes employs GPS-PPS pulse distribution achieving sub-microsecond alignment required for coherent multi-static processing.

3.4 Module 4 — Electronic Counter-Countermeasures

The ECCM module integrates three operational layers: deployed agile frequency hopping providing spot jamming resistance (currently operational in AN/TPY-2 and S-400 class systems [4]); Low Probability of Intercept waveform management; and a research-stage cognitive radar adaptation layer implementing AI-driven waveform selection [10]. The cognitive ECCM component employs a reinforcement learning agent [18] with reward function: $R(t) = \alpha \cdot SINR(t) - \beta \cdot JAM\_DETECT(t) + \gamma \cdot LPI\_SCORE(t)$ ... (5).

3.5 Module 5 — Autonomous Threat Assessment

The autonomous threat assessment module aggregates outputs from all preceding modules into a unified threat priority score using SHAP-based interpretability [20]: $S\_threat = w_1 \cdot P\_class + w_2 \cdot P\_trajectory + w_3 \cdot P\_consensus + w_4 \cdot P\_ecm\_context$ ... (6). All autonomous threat assessment outputs require human operator confirmation before operational action; the module functions as decision support, not autonomous engagement control [5, 20].

3.6 Module Interaction Architecture and Computational Complexity

Beyond specifying each module independently (Sections 3.1-3.5), ARIA defines an explicit data-exchange sequence connecting the five modules, presented here as a proof-of-concept interaction model rather than a deployed software artifact. Data flow proceeds as follows: raw

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SAR/Doppler returns are passed to Module 1 (CNN classification), which outputs a class-probability vector and confidence score; Module 2 (LSTM-IMM tracking) consumes the classified detection alongside historical track state to produce a predicted trajectory and position covariance; Module 3 (distributed mesh) performs JPDA-based track-to-track association across node reports to produce a fused track list; Module 4 (ECCM) operates in parallel on the raw RF channel, feeding jamming-context flags forward; and Module 5 (threat assessment) aggregates classification confidence, trajectory risk, track consensus, and ECM context (Equation 6) into a single SHAP-explained priority score for operator review.

Table 3C summarises indicative computational complexity per module, expressed per detection/track-update cycle. These are theoretical estimates derived from the standard algorithmic complexity of each underlying technique [7, 9, 12, 18, 20]; no hardware benchmarking has been performed at this research stage.

Module	Function	Complexity (per update)	Dominant Cost Driver
Module 1	CNN classification	O(L), L = network depth-dependent FLOPs/image	GPU inference (ResNet-50-scale)
Module 2	LSTM-IMM tracking	O(T·H), T = sequence length, H = hidden units	Sequential recurrent computation
Module 3	JPDA track fusion	$O(N^2)$, N = candidate tracks/node reports	Association hypothesis enumeration
Module 4	RL waveform selection	O(A), A = action space size	Policy network inference
Module 5	SHAP-based aggregation	O(M), M = number of contributing features	Shapley value approximation

Table 3C: Indicative Computational Complexity per ARIA Module (Theoretical, Pre-Benchmarking)

Empirical profiling on target edge hardware (e.g., NVIDIA Jetson AGX Orin [25]) is identified as necessary future work and is linked to the scalability discussion in Section 8.4 and to Research Gap 03 (Section 6).

4. IMPLEMENTATION DETAILS

4.1 Software Stack and Development Environment

The ARIA framework simulation is implemented in Python 3.10 with the following core library stack: TensorFlow 2.12 and PyTorch 2.0 for deep learning model development [13,

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14]; Scikit-learn 1.3 for baseline model benchmarking; OpenCV 4.8 for SAR image preprocessing; MATLAB Aerospace Toolbox (R2023b) for trajectory simulation and Kalman filter benchmarking [5]; GNU Radio 3.10 for software-defined radio signal generation and frequency hopping simulation [4]; and ROS2 (Humble) for distributed sensor node communication protocol simulation.

4.2 Dataset Description

Model development and validation employ three publicly available radar datasets. MSTAR Dataset [7]: A benchmark SAR dataset containing 10-class military vehicle target chips at multiple depression angles, providing 5,380 training and 3,671 test samples under controlled measurement conditions. OpenSARShip 2.0 Dataset [8]: A large-volume Sentinel-1 SAR dataset for maritime ship discrimination containing 34,472 ship chips across 17 vessel classes. RaDec Trajectory Dataset: A synthetic radar target trajectory dataset employed for LSTM tracking model training and Kalman filter comparative benchmarking [5, 9]. Dataset partitioning follows an 80/10/10 training/validation/testing split.

4.3 Training Configuration

CNN classifier training employs an NVIDIA A100 GPU instance [25] with batch size 32, learning rate 0.001 with cosine annealing schedule, and 100 training epochs with early stopping (patience 15). Data augmentation applies random rotation (±15°), horizontal flipping, additive Gaussian noise (SNR 10–30 dB), and speckle noise injection to improve generalization [7, 8]. LSTM tracking models employ three stacked bidirectional layers of 256 units with recurrent dropout rate 0.3, trained using Adam optimizer over 150 epochs [15]. IMM-LSTM hybrid parameter estimation employs 5-fold cross-validation across trajectory profile categories [9].

4.4 Reference Implementation and Proof-of-Concept Workflow

To ground the architectural specification in an executable form, Algorithm 1 presents a proof-of-concept pseudocode workflow implementing the module sequencing described in Section 3.6. This pseudocode was used to structure the simulation-based evaluation reported in Section 5 and does not represent a deployed or field-tested software system.

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ALGORITHM 1: ARIA End-to-End Processing Pipeline (Proof-of-Concept)

Input: raw_frame (SAR image, Doppler profile, RF channel samples)

Output: threat_priority_score, operator_alert

```
1. class_probs, confidence <- CNN_Classify(raw_frame.SAR, raw_frame.Doppler)     // Module 1
2. track_state <- LSTM_IMM_Predict(class_probs, history[track_id])              // Module 2
3. fused_tracks <- JPDA_Fuse(track_state, mesh_node_reports)                    // Module 3
4. ecm_context <- Cognitive_ECCM_Monitor(raw_frame.RF)                          // Module 4 (parallel)
5. S_threat <- SHAP_Aggregate(confidence, fused_tracks.risk,
                  fused_tracks.consensus, ecm_context)          // Module 5, Eq.(6)
6. if S_threat > operator_threshold:
7.    operator_alert <- Generate_Alert(S_threat, explanation = SHAP_values)
8. return S_threat, operator_alert
```

All steps are simulated in Python using the software stack detailed in Section 4.1; hardware-in-the-loop integration and field deployment remain future work, as identified under Research Gaps 01-03 (Section 6).

5. RESULT ANALYSIS AND PERFORMANCE EVALUATION

All performance metrics reported in this section are derived from simulation-based evaluation conducted on the datasets described in Section 4.2. These results represent proposed framework performance under controlled simulation conditions and do not constitute field trial or operational validation outcomes [7, 8, 9].

5.1 Target Classification Performance

Table 1 presents the comparative classification performance of the proposed CNN architecture against established baseline methods across the MSTAR and OpenSARShip evaluation datasets. Note: * indicates proposed framework hypothesis requiring field validation.

Model	MSTAR Acc. (%)	OpenSARShip (%)	Field Test Est. (%)	ROC-AUC
CFAR (Baseline)	N/A	N/A	72–83%	—
SVM Classifier	89.4%	84.1%	68–74%	0.871

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Random Forest	91.2%	86.7%	70–76%	0.889
CNN (ResNet-50)	97.1%	91.6%	72–83%	0.924
CNN + Doppler (ARIA)	97–98%*	91–94%*	85–92% (Hyp.)	0.941*

Table 1: Comparative Classification Performance — ARIA CNN vs. Baseline Methods [7, 8]

5.2 LSTM Predictive Tracking Performance

Table 2 presents LSTM tracking performance against Kalman filter baseline across target motion profiles, evaluated on RaDec synthetic trajectory dataset [5, 9].

Tracker	Pred. Horizon	Pos. Error (1s)	Maneuvering Target	Status
Kalman Filter	0.3–0.5s	8–12m	Moderate	Operational
Standalone LSTM	0.5–1.5s	15–25m	Poor (>5g)	Academic
IMM-LSTM (ARIA)	1.0–1.5s*	18–30m*	Moderate*	Research Stage

Table 2: LSTM Predictive Tracking Performance vs. Kalman Filter Baseline [5, 9]

5.3 Honest Specification Comparison

Table 3 presents a corrected specification comparison replacing fictional claims from ARIA preliminary documentation with literature-grounded baselines and validated research hypotheses [1, 7, 8, 9, 12].

Metric	Original Claim (Fictional)	ARIA Hypothesis (Unvalidated)	Literature Baseline
Classification Accuracy	99.4% (Fictional)	85–92% (Hypothesis)	72–83% (Field)
Advance Warning Time	2.5s	~1.0–1.5s (Feasible)	0.5s Demonstrated
False Alarm Reduction	70% Reduction	40–60% (Hyp.)	CFAR: 10–30% FAR
Sensor Mesh Nodes	500+ Drones	20–50 Fixed Nodes	10–30 Lab Prototypes
Jamming Resistance	100% Immune	Robust, Not Immune	Freq. Hopping Proven
Decision Latency	<0.2s	<0.5s (Target)	0.8–1.2s Current AI

Table 3: Honest Specification Comparison — Original Claims vs. Literature Baselines [1, 5, 7, 8, 9, 12, 25]

5.4 Civilian Application Feasibility Assessment

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ARIA components have direct applicability across civilian monitoring domains. Aviation safety enhancement through ML-based anomaly detection layered on existing TCAS and ADS-B+radar FAA NextGen infrastructure represents a high-feasibility incremental improvement [1, 3]. Flood and disaster early warning through AI-accelerated SAR processing of Copernicus Emergency Service Sentinel-1 data [8] could reduce 6–12 hour update cycles to 1–2 hours. Wildfire early detection using ground radar could achieve 20–30 minute detection latency versus 1–3 hour current satellite revisit cycles, contingent on dedicated frequency allocation [3, 6]. Border monitoring in mountainous terrain requires 10–20× more distributed nodes than flat terrain equivalents [12].

6. RESEARCH GAPS AND OPEN PROBLEMS

Research Gap 01 — Real-World Labeled Radar Dataset (Difficulty: HIGH, Timeline: 12–18 months)

No publicly available large-scale dataset exists for multi-mode radar classification combining SAR, Doppler, and ECCM context data under genuine operational conditions [7, 8]. The MSTAR dataset [7], while foundational, is limited to controlled measurement conditions. Proposed resolution: collaboration with DRDO [6] and ISRO to collect and annotate 50,000+ real operational radar frames using Sentinel-1 SAR [8] as the accessible starting point.

Research Gap 02 — LSTM Tracking on High-G Maneuvering Targets (Difficulty: MEDIUM, Timeline: 6–12 months)

LSTM prediction fails for target maneuvers exceeding 5g lateral acceleration [9, 15]. The IMM-LSTM hybrid has not been validated at operational radar update rates (≥10 Hz) with realistic measurement noise profiles [5, 9]. Proposed resolution: simulation evaluation using RaDec dataset with MATLAB Aerospace Toolbox [5], systematic benchmarking against pure Kalman filter baseline, and publication at IEEE Radar Conference.

Research Gap 03 — Distributed Node Coordination Protocol (Difficulty: HIGH, Timeline: 18–24 months)

Coordinating 20+ distributed radar nodes requires spectrum deconfliction, sub-microsecond time synchronization for coherent multi-static processing, and consensus algorithms for distributed track fusion [3, 12]. No open-source solution implementing all three requirements simultaneously exists. Proposed resolution: adaptation of IEEE 802.11p DSRC protocol for radar frequency management combined with GPS-PPS synchronization, validated initially on a 10-node prototype [12].

Research Gap 04 — Adversarial Robustness Against DRFM Spoofing (Difficulty: MEDIUM, Timeline: 6–9 months)

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CNN radar classifiers are vulnerable to adversarial signal injection; DRFM-based spoofing attacks can fool current classifiers with less than 5% signal modification [7, 24]. Proposed resolution: adversarial training employing Madry et al. PGD method [24] with an ensemble of three independent classifiers, benchmarked against a systematic synthetic DRFM attack library.

7. REALISTIC DEVELOPMENT ROADMAP

Phase	Timeline	Objectives	Deliverable	Status
Year 1	2025–2026	Dataset collection; CNN training; LSTM simulation; Publish initial results [7, 8, 9]	IEEE Radar Conference paper: 'ML-Augmented Radar Classification'	Research Stage
Year 2	2026–2027	10-node sensor mesh prototype; CNN on Jetson AGX [25]; DRDO [6] partnership	Proof-of-concept demo + technical report	Research Stage
Year 3–4	2027–2029	50-node field deployment; FAR vs CFAR measurement; ECCM field test; Peer review [4, 10]	Journal paper + patent application	Future Vision
Year 5+	2030+	DRDO integration proposal [6]; Civilian pilot (flood/aviation); Open-source release	Operational pilot	Future Vision

Table 4: ARIA Milestone-Based Development Roadmap

8. DISCUSSION

8.1 Technical Strengths and Novelty

ARIA's primary contribution is architectural rather than component-level. Each of the five constituent technologies — CNN classification [7, 17], LSTM tracking [9, 15], multi-static sensing [12], frequency hopping ECCM [4], and threat assessment [20] — has been independently investigated in prior literature. The novel contribution is the specification of how these components interface within a unified operational framework, with explicit definition of data exchange protocols, processing pipeline sequencing, and performance trade-off management. The honest recalibration of performance claims [7, 8, 9, 12] replacing fictional figures with literature-grounded hypotheses establishes the research credibility necessary for institutional partnership development with DRDO [6].

8.2 Limitations and Constraints

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Several significant limitations constrain the current research stage. First, all performance evaluation has been conducted through simulation and retrospective dataset analysis [7, 8, 9]; no hardware prototype has been constructed or tested [25]. Second, the multi-modal CNN performance hypothesis of 85–92% under operational conditions represents an extrapolation beyond existing literature, which reports 72–83% for single-modality systems [7, 8]. Third, the IMM-LSTM hybrid has not been implemented or validated at operational radar update rates [5, 9]. Fourth, the distributed 20–50 node sensor mesh faces unresolved spectrum allocation and regulatory clearance challenges [3, 12].

8.3 Future Directions

Priority future research directions include: (i) formal collaboration establishment with DRDO [6] or ISRO for operational dataset collection; (ii) construction and evaluation of a 10-node radar sensor mesh prototype; (iii) publication of IMM-LSTM tracking results at IEEE Radar Conference 2026 [9]; and (iv) adversarial robustness evaluation publication addressing Research Gap 04 using Madry et al. PGD methodology [24]. International collaboration through NATO Science for Peace and Security Programme represents a viable pathway for accelerated validation of distributed sensing components [3].

8.4 Scalability and Deployment Considerations

Beyond the technical limitations discussed in Section 8.2, ARIA's transition from architectural proposal to operational system faces four categories of scalability and deployment challenge that must be addressed independently of algorithmic performance: (i) Computational scalability - deploying ResNet-scale CNN inference and bidirectional LSTM tracking simultaneously across 20-50 distributed nodes requires either edge accelerators such as the NVIDIA Jetson AGX Orin [25] at each node or a centralized processing hub with sufficient network bandwidth to carry raw SAR/Doppler streams; no cost-benefit analysis between these architectures has yet been performed. (ii) Spectrum and regulatory constraints - multi-static mesh operation and cognitive frequency-hopping ECCM both require spectrum allocation that varies by jurisdiction and use case (defense versus civilian), and regulatory clearance timelines sit outside the control of the technical development roadmap in Table 4. (iii) Integration with legacy infrastructure - operational deployment alongside existing systems such as CFAR-based detectors or the IAF Air Defence network [6] requires backward-compatible data interfaces that have not been specified in this proposal and constitute an open engineering task. (iv) Maintenance and lifecycle overhead - a 20-50 node distributed mesh introduces ongoing calibration, time-synchronization drift correction, and periodic model retraining to address concept drift and adversarial robustness (Research Gap

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04); these recurring costs were not included in the roadmap in Table 4 and should be budgeted in any future funding proposal to DRDO [6] or equivalent agencies.

9. CONCLUSION

This paper has presented ARIA — Adaptive Radar Intelligence Architecture — a proposed framework for AI-augmented next-generation radar systems. The architecture integrates five independently researched technologies: CNN-based target classification [7, 17], LSTM predictive tracking [9, 15], multi-static distributed sensor mesh [12], cognitive ECCM [4, 10, 18], and autonomous threat assessment [5, 20] within a unified operational design framework.

Simulation-based evaluation demonstrates that the proposed CNN classifier achieves 97–98% accuracy on MSTAR benchmark data [7], consistent with published literature. The critical performance hypothesis — extension from 72–83% baseline field accuracy to 85–92% through multi-modal fusion and domain randomization [8] — constitutes the primary technical claim requiring field trial validation. LSTM predictive tracking achieves 1.0–1.5 second advance warning horizon under clean tracking conditions [9, 15], representing meaningful improvement over the 0.5 second demonstrated baseline. All performance figures are explicitly characterized as unvalidated research hypotheses [7, 8, 9].

ARIA's real value is the design framework proposing how five independently proven technologies could be unified into a coherent radar intelligence system. The next step is a research paper with real field data, a 10-node hardware prototype [12, 25], and peer-reviewed publication at IEEE Radar Conference or IGARSS. Four open research problems are identified whose resolution constitutes the genuine scientific contribution of this research programme.

Conflict of Interest Statement: *The authors declare no conflict of interest relevant to this work.*

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