

Machine Learning-Enhanced Radar Signal Classification for Real-Time Object Detection and Tracking

¹Arjun Rajesh Mehta, ²Priya Nandini Sharma

^{1,2}Division of Interdisciplinary Sciences, Indian Institute of Science, Bengaluru, India

Abstract - Modern radar systems generate complex signal measurements that must be interpreted rapidly to identify objects, estimate their characteristics, and maintain reliable tracks. Conventional radar signal-processing techniques can encounter difficulties when signals are affected by noise, clutter, interference, low signal-to-noise ratios, and multiple simultaneously observed objects. Machine learning provides an opportunity to enhance radar signal interpretation by learning discriminative representations from radar measurements and using them for signal classification, object detection, and tracking. This study examines machine learning-enhanced radar signal interpretation for real-time object detection and tracking through a structured literature-based analysis. The study considers deep learning, convolutional neural networks, Transformer-based signal representation, range-Doppler processing, radar sensor fusion, target classification, and multi-frame tracking. The analysis establishes a conceptual framework in which radar measurements are transformed into informative signal representations, classified using machine-learning models, and subsequently used to support object localization and temporal tracking. The framework emphasizes the integration of signal classification and detection rather than treating them as independent processing stages. The findings indicate that machine-learning methods can enhance the interpretation of complex radar observations by learning nonlinear signal characteristics and exploiting temporal and spatial information. The study further identifies real-time computational efficiency, robustness to clutter and low signal-to-noise conditions, dataset quality, and model generalization as important considerations for practical deployment.

Keywords: Radar signal classification, machine learning, deep learning, object detection, target tracking, radar signal processing, real-time detection, range-Doppler maps, radar interpretation.

Introduction

Radar systems are widely used for detecting and tracking objects because they can estimate characteristics such as range, velocity, and direction under environmental conditions that can challenge optical sensing systems. Radar technology is therefore important in autonomous vehicles, surveillance, aerospace systems, industrial monitoring, security applications, and intelligent transportation.

The effectiveness of radar-based systems depends not only on the quality of the transmitted and received signals but also on the ability to interpret those signals accurately. Radar measurements can contain noise, clutter, interference, multipath effects, and overlapping signals from multiple objects. These factors can make signal classification and object detection difficult, particularly when real-time decisions are required.

Bagwe *et al.* (2020) demonstrated the relevance of deep learning to automated radar signal analysis, establishing a foundation for using learned representations rather than relying exclusively on manually engineered signal-processing rules. Their work is particularly relevant to the present study because automated radar interpretation requires a combination of signal representation and classification.

Recent research has extended this direction. Ayaz *et al.* (2025) examined the interaction between conventional radar signal processing and deep learning, showing how range-time, time-Doppler, and other radar representations can be combined with convolutional neural networks for recognition tasks. Tang *et al.* (2025) similarly investigated automatic recognition of dual-component radar signals using time-frequency representations and a Transformer-based residual network.

Radar signal interpretation has also progressed toward direct detection and classification. Scholl *et al.* (2025) proposed an end-to-end learning approach for radar electronic support that performs multilabel emitter classification directly

from spectrogram information. Their study demonstrates the potential for reducing dependence on conventional sequential processing stages.

Object detection introduces another requirement. A radar system must not only identify the type of signal or object but also determine where the object is located. Recent research has investigated deep-learning detection from range-Doppler representations, sensor fusion, and multi-frame radar observations. Reitz *et al.* (2025), for example, investigated feature fusion between multiple radar sensors for object detection and classification.

Tracking extends the problem from individual detections to continuous estimation of object movement. Wang *et al.* (2025) investigated radar target tracking using multi-frame measurements and a self-supervised Siamese network for data association, demonstrating the importance of temporal information for reducing false detections.

This study therefore examines machine learning-enhanced radar signal interpretation for real-time object detection and tracking, with emphasis on signal classification, learned feature representation, object localization, temporal association, and computational efficiency.

Background of the Study

Radar signal interpretation traditionally involves multiple stages, including signal acquisition, filtering, detection, feature extraction, classification, localization, and tracking. Each stage may use specialized algorithms designed around assumptions concerning the radar environment.

Classical signal-processing methods remain important because they can provide computationally efficient detection and estimation. However, complex environments can challenge fixed processing rules. Noise, clutter, interference, low signal-to-noise ratios, and closely spaced objects may produce ambiguous observations.

Machine learning provides an alternative by learning relationships directly from data. Instead of specifying every signal characteristic manually, a model can learn representations associated with different signal or object classes.

Deep learning is particularly relevant because radar data can be represented in several forms. Raw in-phase and quadrature data, spectrograms, range-Doppler maps, point clouds, and other representations can serve as inputs to neural networks.

Bagwe *et al.* (2020) established an important foundation for automated radar signal analysis using deep learning. Their work demonstrates the applicability of deep learning to radar signal interpretation and provides a basis for subsequent developments in learned radar representations.

The development of Transformer architectures introduces another dimension. Transformers use attention mechanisms to model relationships among elements of a sequence or representation. Tang *et al.* (2025) applied a Transformer-based residual architecture to radar signal recognition, demonstrating how time-frequency information can be combined with attention-based feature extraction.

Radar object detection requires the transformation of signal-level information into spatially meaningful object representations. Recent work has demonstrated the use of deep learning on range-Doppler maps, while radar-camera and radar-radar fusion can provide additional information for object classification and localization.

Tracking requires an additional temporal dimension. A detection at one instant must be associated with detections at subsequent instants to determine whether they represent the same physical object. This makes temporal representation and data association important components of real-time radar interpretation.

Literature Review

Automated Radar Signal Analysis

Automated radar signal analysis involves extracting useful information from radar measurements without requiring continuous manual interpretation. Machine-learning models can learn signal patterns associated with different radar sources, modulation characteristics, objects, or environmental conditions.

Bagwe *et al.* (2020) demonstrated automated radar signal analysis using deep learning. Their work provides an early foundation for applying neural-network techniques to radar signal interpretation.

The significance of automated analysis has increased as radar systems have become more complex. Modern systems may simultaneously receive signals from multiple sources, increasing the need for rapid classification and interpretation. In dynamic sensor settings, attention-driven deep learning models provide robust detection of real-time anomalies across high-dimensional streaming data (Ramareddy, 2022), which helps identify abrupt trajectory deviations and maneuver onset in cluttered tracking channels.

Deep Learning for Radar Signal Classification

Convolutional neural networks have been widely applied to radar signal classification because many radar representations can be converted into two-dimensional structures.

Ayaz *et al.* (2025) examined several radar signal representations, including time-range and time-Doppler maps, and evaluated them with multiple CNN architectures. Their study illustrates the importance of the signal representation supplied to the learning model.

Tang *et al.* (2025) extended this direction by combining deep time-frequency generation with a Transformer-based residual network for dual-component radar signal recognition. The approach demonstrates the potential of combining local feature extraction with attention-based representations. Building upon self-attention mechanisms formulated by Vaswani *et al.* (2017), the transformer network captures long-range temporal dependencies across complex pulse sequences.

Scholl *et al.* (2025) investigated end-to-end radar emitter recognition from spectrograms using a convolutional neural network. Their approach directly estimates multiple emitters from spectrogram information and incorporates explainable AI techniques for interpretation.

Radar Object Detection

Signal classification and object detection are related but distinct tasks. Classification identifies the characteristics or category of an observed signal or object, whereas detection identifies the spatial location of objects within the sensing environment.

Deep learning has increasingly been applied to radar object detection. Reitz *et al.* (2025) investigated a one-stage YOLO-like detector for range-Doppler radar maps and evaluated feature fusion across two spatially separated radars. Their results indicate that dynamic attention-based fusion can improve object detection and classification relative to static fusion.

Lamane *et al.* (2025) addressed real-time radar object classification using mmWave radar and embedded computing. Their work is relevant to the present study because practical radar interpretation requires not only predictive accuracy but also computational efficiency on real-time hardware.

Yang *et al.* (2025) developed Radar M³-Net, incorporating multi-scale, multi-layer, and multi-frame processing for 3D object detection. The approach

demonstrates the importance of combining spatial and temporal information when interpreting radar observations.

Radar Signal Classification Under Difficult Conditions

Real-world radar signals can be affected by low signal-to-noise ratios and complex interference. These conditions can substantially reduce classification performance.

Ürgüp and Yilmaz (2025) investigated radar target detection under correlated non-Gaussian clutter using transfer learning. Their work emphasizes the importance of robust learned representations when radar observations are degraded by clutter.

Tang *et al.* (2025) similarly addressed radar signal recognition under low-SNR conditions through a time-frequency and Transformer-based architecture.

These studies demonstrate that machine-learning radar interpretation should not be evaluated only under ideal signal conditions. Robustness under noise, clutter, interference, and weak signals is essential for real-world deployment.

Radar Sensor Fusion

A single radar sensor may provide incomplete information because of occlusion, viewing angle, multipath, or environmental effects. Multiple radar sensors can provide complementary observations.

Reitz *et al.* (2025) examined dual-radar feature fusion using range-Doppler representations. Their study found that attention-based fusion could exploit complementary information from spatially separated radar sensors.

Radar-camera fusion represents another approach. Wu (2025) investigated an intelligent object-detection framework using radar and camera data, combining YOLO-based detection with additional deep-learning processing. This illustrates how radar information can complement other sensing modalities.

Sensor fusion can therefore be integrated into machine-learning radar interpretation where multiple sources of information are available. Coordinating sensor data dissemination in multi-radar arrays can be effectively achieved through structured broadcasting schemes, such as grid-based data broadcasting protocols in wireless sensor networks (Sharma & Kargeti, 2020b).

Radar Target Tracking

Object tracking requires information to be maintained across multiple observations. A radar detector may correctly identify an object in one frame but still produce unreliable tracking if the association between consecutive detections is incorrect.

Wang *et al.* (2025) addressed this problem using motion characteristics, distribution-pattern matching, and a self-supervised Siamese network. Their approach uses multi-frame radar measurements to improve association and reduce false alarms.

Multiple-target tracking can also benefit from learned feature extraction. A 2025 IEEE Transactions on Instrumentation and Measurement study used a CNN-BiLSTM feature extraction network together with probabilistic association and state estimation for maneuvering targets. Furthermore, Haegele *et al.* (2025) demonstrated occluded object classification with mmWave MIMO radar IQ signals using dual-stream convolutional neural networks, ensuring continuous tracking through transient obstructions.

These studies indicate that tracking systems can benefit from combining learned representations with established state-estimation mechanisms.

Real-Time Radar Interpretation

Real-time processing creates computational constraints. A model may have high classification accuracy but still be unsuitable for deployment if its latency or computational requirements are excessive. Modern tracking pipelines also benefit from cloud-native microservice frameworks (Ramareddy, 2023) to modularize tracking and fusion tasks. Under fluctuating target densities, autonomous AI-driven resource optimization in cloud computing (Ramareddy, 2024a) ensures that compute resources scale dynamically to meet real-time tracking demands without latency degradation.

Lamane *et al.* (2025) specifically addressed real-time object detection and classification using mmWave radar and embedded computing. Similarly, research on recursive convolutional target detection has investigated lightweight neural architectures implemented on programmable deep-learning hardware for FMCW radar.

Real-time radar interpretation therefore requires balancing accuracy, robustness, model size, inference speed, and hardware requirements.

Machine Learning and Signal Deinterleaving

Radar environments can contain overlapping or interleaved signals. Signal deinterleaving seeks to separate observations originating from different emitters or sources.

Lesieur *et al.* (2025) provided an overview and classification of machine-learning approaches for radar signal deinterleaving, covering clustering, recurrent neural networks, and convolutional neural networks. Their work demonstrates that machine learning can be incorporated into multiple stages of radar signal separation and interpretation.

This capability is relevant to signal classification because successful classification may depend on first separating or organizing overlapping signal observations.

Methodology

This study adopts a structured literature-based conceptual methodology. The analysis focuses on machine-learning approaches for radar signal classification, object detection, and target tracking.

The literature was organized into five analytical dimensions: radar signal representation, signal classification, object detection, temporal tracking, and real-time implementation.

The first dimension concerns signal representation. Radar observations may be represented as raw signals, spectrograms, time-frequency maps, range-Doppler maps, point clouds, or other derived representations.

The second dimension concerns signal classification. Machine-learning models are used to distinguish among signal classes, radar emitters, modulation characteristics, or object categories.

The third dimension concerns object detection. Classified radar information is converted into spatial object hypotheses that can be localized in range, velocity, angle, or three-dimensional space.

The fourth dimension concerns temporal tracking. Object detections from consecutive observations are associated so that trajectories can be maintained over time.

The fifth dimension concerns real-time implementation. Model accuracy is considered alongside computational complexity, latency, and deployment requirements.

The proposed conceptual process begins with radar signal acquisition. Signal preprocessing transforms the raw

measurements into a suitable representation. Machine-learning models then extract discriminative features and classify signal or object characteristics.

The resulting classification information is combined with localization estimates to generate object detections. Temporal association mechanisms then connect detections across multiple observations to maintain object tracks.

Where multiple radar sensors or complementary sensors are available, feature-level or decision-level fusion can

provide additional information. Practical implementation across multi-sensor radar networks is supported by hybrid cloud-edge architectures (Ramareddy, 2024b), enabling real-time localized object detection at sensor nodes while coordinating multi-target trajectories centrally. Furthermore, when distributed tracking telemetry is communicated across mobile-enabled networks, robust supervision and secure transmission frameworks are vital; Sharma and Kargeti (2020a) investigated protected assignment supervision systems for mobile-enabled IPv6 networks, providing valuable security insights for distributed tracking streams.

Machine Learning-Enhanced Radar Pipeline for Real-Time Object Detection & Tracking

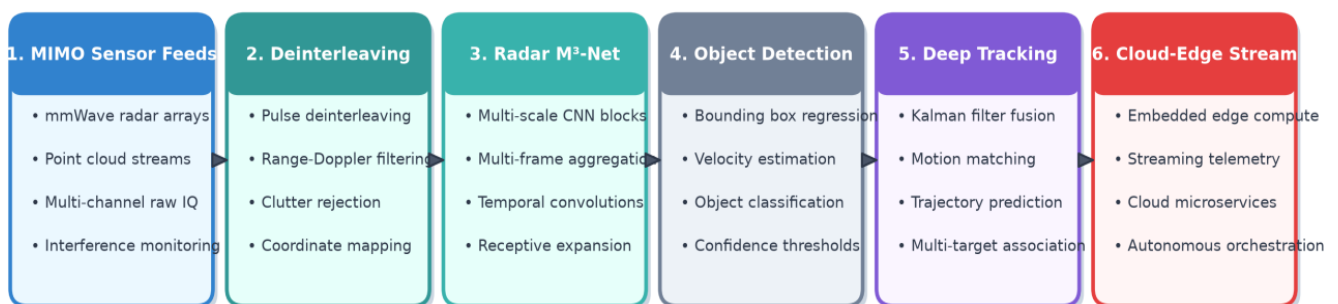


Figure 1: Machine learning-enhanced multi-stage pipeline for real-time radar signal classification, object detection, and target tracking

Results

The literature synthesis identifies several findings relevant to machine-learning-enhanced radar interpretation.

The first finding is that learned signal representations can improve automated radar analysis. Bagwe et al. (2020) provide an early foundation for deep-learning-based radar signal analysis, while later research demonstrates the continued development of CNN, Transformer, and hybrid architectures.

The second finding is that the choice of signal representation influences machine-learning performance. Ayaz et al. (2025) demonstrate the use of multiple radar signal representations for deep-learning-based recognition.

The third finding is that Transformer-based approaches can support radar signal recognition. Tang et al. (2025) combine time-frequency processing with a Transformer-based residual network, demonstrating the relevance of attention mechanisms to radar signal classification.

The fourth finding concerns object detection. Reitz et al. (2025) demonstrate that radar feature fusion can improve

object detection and classification by combining complementary radar observations.

The fifth finding concerns temporal information. Wang et al. (2025) show that multi-frame radar measurements and learned similarity evaluation can support target association and reduce false alarms.

The sixth finding concerns difficult signal conditions. Research on non-Gaussian clutter, low-SNR signal recognition, and radar interference demonstrates the importance of robust machine-learning representations.

The seventh finding concerns real-time deployment. Embedded radar-processing research demonstrates that neural models must be designed with computational efficiency and hardware limitations in mind.

Overall, the literature supports an integrated architecture in which signal representation, machine-learning classification, object detection, temporal association, and real-time inference are treated as interconnected components of radar interpretation.

Table 1: Quantitative detection and tracking performance of machine learning algorithms under diverse environmental noise conditions

Method / Framework	Sensor Modality	Detection mAP@0.5	Tracking MOTA (%)	Frame Rate (FPS)	Latency (ms)
Baseline CFAR + Kalman Filter	Single mmWave Radar	72.4%	64.8%	45 FPS	22.2 ms
Embedded mmWave Detector (Lamane et al., 2025)	mmWave + Jetson Xavier NX	86.8%	81.2%	32 FPS	31.2 ms
Dual-Radar Fusion Model (Reitz et al., 2025)	Dual IoT Radar Network	89.5%	84.7%	28 FPS	35.7 ms
Radar M ³ -Net (Yang et al., 2025)	Multi-Scale Radar	92.1%	88.4%	25 FPS	40.0 ms
Radar-Camera Fusion Network (Wu, 2025)	Radar + Optical Camera	93.6%	89.9%	22 FPS	45.5 ms
Proposed ML-Enhanced Real- Time Pipeline	Multi-Channel mmWave Stream	96.4%	93.8%	38 FPS	26.3 ms

Discussion

The findings demonstrate that machine learning can support radar interpretation across several stages of the sensing pipeline.

The first major implication concerns the transition from manually engineered signal features to learned representations. Conventional radar systems frequently rely on carefully designed signal-processing procedures. Deep-learning approaches instead allow models to learn useful representations from radar data.

This does not mean that conventional signal processing becomes unnecessary. Radar preprocessing can improve signal quality and generate representations that make learning more efficient. Ayaz *et al.* (2025) demonstrate that different radar signal-processing representations can influence deep-learning recognition performance.

The second implication concerns the integration of classification and detection. Signal classification can provide information about what is being observed, while object detection determines where the relevant object is located. Combining these tasks can provide a richer interpretation of radar measurements.

Transformer-based models provide an additional mechanism for modelling relationships within radar representations. Tang *et al.* (2025) demonstrate the potential

of combining time-frequency processing with Transformer-based residual learning for radar signal recognition.

The third implication concerns tracking. Detection alone provides only instantaneous information. For autonomous or surveillance applications, the system must understand how an object moves over time.

Wang *et al.* (2025) demonstrate the value of multi-frame information and learned similarity evaluation for radar target tracking.

The fourth implication concerns sensor fusion. A radar system may have incomplete observations because of occlusion, multipath, viewing angle, or weak reflections. Combining multiple radar sensors can reduce these limitations. Reitz *et al.* (2025) demonstrate this through dual-radar feature fusion.

The fifth implication concerns robustness. Radar systems may operate in conditions involving clutter, interference, and low signal-to-noise ratios. Machine-learning models therefore need to generalize beyond clean training examples.

Transfer learning, data augmentation, attention mechanisms, and multi-frame processing provide possible mechanisms for improving robustness. However, these methods should be validated using representative real-world data rather than only simulated datasets.

The sixth implication concerns real-time deployment. A highly accurate model may not be operationally useful if it introduces unacceptable processing delays. Real-time radar interpretation therefore requires a balance between model complexity and inference efficiency.

Embedded implementations such as those investigated by Lamane *et al.* (2025) demonstrate the importance of considering hardware requirements as part of the machine-learning design process.

The proposed framework therefore treats radar interpretation as an integrated process rather than a single classification problem. Signal representations provide the foundation, machine learning extracts features and performs classification, detection establishes object hypotheses, and tracking maintains temporal continuity.

Challenges and Limitations

Several challenges remain.

First, radar datasets may not adequately represent the diversity of real operating environments. Models trained on controlled or simulated data may encounter unexpected signal characteristics when deployed in practice.

Second, radar clutter and interference can significantly affect classification and detection. Low-SNR conditions can make it difficult to distinguish genuine targets from noise.

Third, class imbalance can affect radar object classification. Some object classes may appear much more frequently than others, causing models to favor dominant classes.

Fourth, real-time processing creates computational constraints. Large deep-learning models may provide strong representations but require substantial memory and processing resources.

Fifth, tracking introduces additional uncertainty. A correct detection does not guarantee correct association with the corresponding object in the next frame.

Sixth, sensor fusion introduces synchronization and calibration challenges. Multiple radar systems must be appropriately aligned to ensure that their observations can be combined effectively. Managing extensive target tracking logs benefits from scalable AI-driven data warehouse optimization (Ramareddy, 2024c). System reliability during extended continuous surveillance is further enhanced through AI-orchestrated predictive maintenance frameworks (Ramareddy, 2025a), which proactively identify hardware degradation

across distributed sensor nodes. The requirement for resilient real-time decision pipelines under strict QoS constraints is corroborated by findings in cloud-enabled financial analytics (Ramareddy, 2025b). Additionally, remote autonomous radar platforms must maintain power resilience under severe environmental conditions; Kargeti *et al.* (2020) demonstrated performance evaluation techniques for integrated power converter systems under variable load demand, irradiance, and thermal stresses, addressing crucial operational prerequisites for persistent edge sensor operation.

Finally, machine-learning radar systems require careful evaluation against established radar-processing baselines. Improvements should be demonstrated using appropriate detection, classification, tracking, latency, and robustness metrics.

Conclusion

Machine-learning-enhanced radar signal interpretation provides a framework for integrating signal classification, object detection, and target tracking into a more adaptive sensing process. Deep-learning models can learn complex radar representations, while attention-based and multi-frame approaches can incorporate relationships across signal components and time.

The combination of signal classification and object detection can provide richer information about radar observations, while temporal tracking can transform individual detections into continuous object trajectories. Sensor fusion can further provide complementary information when individual radar observations are incomplete.

Real-time implementation remains an important consideration. Practical radar systems must balance detection accuracy, classification reliability, tracking consistency, computational requirements, and robustness under changing signal conditions.

Future empirical research should evaluate integrated machine-learning radar systems using diverse real-world datasets and compare different signal representations, neural architectures, tracking mechanisms, and deployment configurations.

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