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REAL-TIME ANOMALY DETECTION IN FMCW RADAR SYSTEMS USING HYBRID AUTOENCODER-LSTM ALGORITHM – A REVIEW

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ABSTRACT

Frequency-Modulated Continuous-Wave (FMCW) radar systems are widely used in autonomous vehicles, aerospace navigation, industrial automation, robotics, surveillance, and defense applications because they provide accurate range estimation, velocity measurement, and real-time object detection. However, their reliability can be affected by hardware degradation, environmental interference, signal distortion, electromagnetic disturbances, calibration errors, and operational instability. Traditional anomaly detection methods based on threshold monitoring and statistical signal analysis often fail to detect subtle or evolving abnormalities under dynamic conditions. This review presents a compact analysis of artificial intelligence-based anomaly detection techniques for FMCW radar systems, with emphasis on Autoencoder, Long Short-Term Memory (LSTM), and Hybrid Autoencoder-LSTM frameworks. Autoencoders support reconstruction-based spatial feature learning, whereas LSTM networks model temporal dependencies in sequential radar signals. The hybrid approach combines these capabilities and provides improved robustness, adaptability, and predictive maintenance support. The review discusses anomaly sources, motivation for AI-based detection, deep learning frameworks, performance evaluation practices, application areas, research gaps, and future directions. Comparative evidence from recent studies indicates that Hybrid Autoencoder-LSTM models generally outperform conventional machine learning methods such as Support Vector Machine and Random Forest in terms of detection accuracy, false-alarm control, and real-time applicability. The paper further highlights challenges related to dataset availability, computational complexity, model interpretability, cybersecurity threats, and deployment on edge devices. Overall, AI-enabled hybrid deep learning frameworks provide a scalable and intelligent direction for reliable anomaly detection and predictive maintenance in next-generation FMCW radar systems.

KEYWORDS: FMCW Radar, Anomaly Detection, Artificial Intelligence, Autoencoder, LSTM, Deep Learning, Predictive Maintenance, Radar Signal Processing.

1. INTRODUCTION

The significance of this review is also linked to the increasing dependence of modern sensing platforms on continuous data-driven monitoring. Radar systems are no longer used only as isolated sensing components; they are now integrated with decision-support modules, autonomous control units, and predictive maintenance platforms. Therefore, anomaly detection must not only identify abnormal signals but also support operational reliability, early warning generation, and maintenance planning. AI-based radar analytics provides this capability by learning from historical and real-time signal behaviour and by improving detection consistency across different operational scenarios.

Frequency-Modulated Continuous-Wave (FMCW) radar has become an essential sensing technology for intelligent and safety-critical systems. It continuously transmits frequency-modulated signals and estimates target range and velocity by analyzing the frequency difference between transmitted and received signals. Because of compact design, low power consumption, continuous monitoring capability, and high-resolution sensing, FMCW radar is widely adopted in autonomous vehicles, aerospace navigation, industrial automation, robotics, defense surveillance, smart transportation, and healthcare monitoring applications [1].

Reliable operation of FMCW radar is especially important in autonomous and mission-critical environments. In autonomous vehicles, radar supports adaptive cruise control, collision avoidance, obstacle detection, lane assistance, and blind-spot monitoring. In aerospace and defense systems, radar assists target tracking, navigation support, environmental monitoring, and surveillance. Any anomaly in radar signals may reduce detection accuracy, generate false alarms, or lead to unsafe operational decisions [2].

Radar anomalies may arise from several sources, including hardware degradation, thermal noise, electromagnetic interference, multipath propagation, environmental disturbances, calibration instability, and signal distortion. Traditional methods such as threshold-based monitoring, statistical analysis, and manual waveform inspection are useful for simple fault conditions but are less effective for subtle, gradual, or previously unseen abnormalities. These methods also require manual feature engineering and continuous expert supervision [3]. Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) techniques provide an adaptive alternative by learning complex signal behavior directly from radar data. While classical ML models such as Support Vector Machine, Random Forest, and Decision Tree improve automatic classification, they struggle to model sequential temporal patterns. Deep learning frameworks, particularly Autoencoders and LSTM networks, overcome these limitations by learning spatial and temporal representations from radar signals [4], [5]. This review focuses on AI-based anomaly detection for FMCW radar, especially Hybrid Autoencoder-LSTM frameworks for robust monitoring and predictive maintenance.

2. FMCW Radar and Anomaly Detection Challenges

Another practical challenge is the similarity between benign operational variation and true anomaly behaviour. For example, temporary weather-related signal variation may resemble sensor degradation, while multipath reflections may appear similar to interference-based anomalies. This overlap makes simple classification difficult and increases the risk of both false-positive and false-negative outcomes. A reliable anomaly detection system must therefore distinguish between acceptable environmental variation and abnormal signal behaviour that requires corrective action.

FMCW radar systems operate in complex and dynamic environments where signal behavior is continuously influenced by objects, weather, reflections, interference, and sensor conditions. Unlike simple static sensing systems, radar signals contain amplitude, phase, Doppler, frequency, and temporal waveform information. This high-dimensional and sequential nature makes anomaly detection a difficult task, particularly when abnormal behavior develops gradually over time [1].

Environmental interference is one of the most common challenges. Rain, fog, dust, snow, atmospheric variations, and reflective surfaces can distort radar signals and create multipath effects. In autonomous vehicle scenarios, nearby vehicles, buildings, road barriers, and metallic objects may cause signal reflection and interference. These disturbances can appear similar to actual faults, increasing the difficulty of reliable anomaly classification [2], [3].

Hardware degradation also affects long-term radar reliability. Antennas, transmitters, receivers, oscillators, and signal processing modules may deteriorate due to aging, overheating, mechanical stress, or operational fatigue. Early-stage degradation often produces small signal deviations that are difficult to distinguish from normal fluctuations. Conventional threshold-based systems may detect only severe failures, while missing gradually evolving faults [4].

Additional challenges include real-time processing constraints, class imbalance, dataset labeling difficulty, and model interpretability. Radar systems used in autonomous vehicles and aerospace platforms require low-latency anomaly detection, but many deep learning models demand significant computation. Public radar datasets may also lack sufficient real-world anomalies, and black-box AI models may reduce trust in safety-critical applications. These issues motivate the development of adaptive, efficient, and explainable AI-based monitoring frameworks [5]–[10].

3. Motivation for AI-Based Detection

AI-based detection is further motivated by the need for scalable monitoring across large fleets of radar-enabled systems. In autonomous transportation, industrial facilities, and defense networks, hundreds or thousands of radar sensors may operate simultaneously. Manual inspection of each radar signal is impractical in such environments. Learning-based anomaly detection enables automated and consistent monitoring at scale, allowing operators to prioritize high-risk devices and respond before failures affect system performance.

The motivation for AI-based anomaly detection arises from the growing complexity of radar environments and the limitations of conventional monitoring systems. Traditional methods rely on fixed thresholds, statistical rules, or manually selected features. Such approaches cannot easily adapt to changes in weather, object motion, sensor aging, interference, and operational context. AI-based models can learn hidden signal patterns from data and continuously improve detection capability under changing conditions [1], [2].

Machine learning models introduced automated pattern recognition for radar anomaly detection, but many still depend on handcrafted features and labeled datasets. In real radar systems, collecting and labeling every possible anomaly is difficult, expensive, and sometimes impractical. Unsupervised and semi-supervised learning approaches are therefore important because they can learn normal radar behavior and detect deviations without requiring large labeled anomaly datasets [3].

Autoencoders are particularly useful because they learn compact representations of normal radar signals and identify anomalies through reconstruction error. When abnormal signals deviate from learned normal patterns, reconstruction error increases, enabling detection of unknown or unseen anomaly types. LSTM networks add the ability to learn temporal dependencies, making them suitable for sequential radar data where faults evolve gradually across time [4]–[6].

Hybrid Autoencoder-LSTM frameworks combine spatial reconstruction learning with temporal sequence modeling. This hybrid design improves detection of both static waveform distortions and dynamic degradation patterns. It also supports predictive maintenance by identifying early-stage faults before complete failure occurs. In mission-critical applications, this capability reduces downtime, improves safety, and enables proactive maintenance planning [7]–[10].

4. Deep Learning-Based Framework

The implementation workflow usually begins with signal cleaning and normalization because raw radar data may contain noise, missing values, and inconsistent amplitude scales. After preprocessing, signals are segmented into fixed-length windows so that both instantaneous waveform characteristics and temporal sequences can be analyzed. This window-based representation is particularly useful for LSTM models because it preserves chronological relationships between consecutive radar observations. The final anomaly decision is commonly generated by combining reconstruction error, learned temporal features, and classification probabilities.

Deep learning-based radar anomaly detection frameworks generally include data acquisition, preprocessing, feature learning, anomaly scoring, and classification or decision generation. Radar signals are first collected from sensors or public datasets and then processed through normalization, filtering, segmentation, and feature organization. Preprocessing improves signal consistency and prepares sequential data for learning-based analysis [1].

Autoencoders form a central component of many unsupervised anomaly detection systems. The encoder compresses input radar signals into latent representations, while the decoder reconstructs the original signal from this compressed form. During training, the model learns normal signal behavior by minimizing reconstruction loss. During testing, abnormal signals produce higher reconstruction errors because they do not match learned normal patterns [2], [3]. LSTM networks complement autoencoders by modeling temporal relationships in sequential radar observations. FMCW radar signals are time-dependent, and many anomalies appear as gradual changes rather than isolated events. LSTM memory cells and gating mechanisms allow the model to retain historical signal information and detect evolving degradation, instability, or interference patterns [4], [5].

In Hybrid Autoencoder-LSTM architectures, the autoencoder extracts compact spatial features and the LSTM analyzes their temporal evolution. This integrated structure captures both waveform characteristics and sequential changes, improving robustness in noisy and dynamic radar environments. The final decision layer may classify signals into normal and anomalous categories or into multiple anomaly classes such as hardware fault, interference, environmental disturbance, and calibration instability [6], [7]. Recent studies also explore attention mechanisms, Transformer models, edge AI deployment, and federated learning for improving radar anomaly detection. Attention mechanisms help the model focus on critical signal regions, while edge AI supports low-latency inference on embedded devices. Federated learning enables collaborative model training without sharing raw radar data, which is useful for privacy-sensitive and distributed monitoring environments [8]–[12].

5. Performance Analysis

A reliable performance analysis should also consider operational cost and deployment feasibility. A model that achieves high accuracy but requires excessive computation may be unsuitable for embedded radar platforms. Similarly, a model with strong recall but excessive false positives may overwhelm operators and reduce trust in the monitoring system. Therefore, the best framework is not necessarily the most complex architecture, but the one that balances accuracy, latency, robustness, interpretability, and maintenance usefulness under realistic deployment constraints.

Performance evaluation is essential for determining the practical usefulness of AI-based radar anomaly detection models. Common metrics include accuracy, precision, recall, F1-score, reconstruction error, false-alarm rate, confusion matrix analysis, computational efficiency, and real-time detection latency. Accuracy provides an overall measure, but precision and recall are especially important in safety-critical systems where both false alarms and missed anomalies can have serious consequences [1], [2]. Traditional threshold-based and statistical methods often show limited performance under dynamic conditions because they cannot adequately represent complex signal variations. Classical ML models such as SVM and Random Forest improve automated classification but still depend on handcrafted features and may struggle with sequential signal behavior. Autoencoder-based models improve unknown anomaly detection through reconstruction learning, while LSTM models improve temporal analysis [3]–[5].

Comparative findings from recent studies indicate that Hybrid Autoencoder-LSTM models achieve stronger and more stable performance than standalone methods. The hybrid framework benefits from the autoencoder's latent spatial representation and the LSTM's temporal dependency modeling. This enables reliable detection of signal interference, hardware degradation, and gradual operational instability [6]–[8].

Table 1: Comparative Performance of AI-Based Radar Anomaly Detection Models.

Model	Accuracy	Precision	Recall	F1-Score
Threshold-Based Methods	72%–80%	Moderate	Low	Low
Support Vector Machine	85%–88%	0.86	0.85	0.85
Random Forest	84%–87%	0.84	0.83	0.83
Autoencoder	90%–92%	0.90	0.89	0.89
LSTM	91%–93%	0.91	0.92	0.91
Hybrid Autoencoder-LSTM	94%–96%	0.94	0.94	0.94

6. Significance and Applications

The practical value of such systems is especially visible in predictive maintenance. Instead of waiting for complete radar failure, anomaly trends can be monitored over time to identify early degradation. This supports scheduled maintenance, avoids unexpected downtime, and improves life-cycle management of radar equipment. In industrial and transportation environments, even small improvements in fault prediction can produce significant benefits in cost reduction, safety assurance, and operational continuity.

AI-based anomaly detection in FMCW radar systems has strong significance for safety, reliability, and predictive maintenance. In autonomous vehicles, reliable radar operation supports collision avoidance, adaptive cruise control, lane assistance, blind-spot monitoring, and obstacle detection. Early anomaly detection reduces the risk of false alarms, missed detections, and unsafe navigation decisions [1], [2].

Aerospace and defense applications also depend on dependable radar monitoring for navigation support, target tracking, surveillance, and situational awareness. Hybrid deep learning frameworks can identify subtle signal degradation and dynamic anomalies in complex environments, improving mission reliability and operational resilience [3]. Industrial automation systems benefit from predictive maintenance, where early detection of radar faults prevents downtime, reduces repair cost, and improves production continuity [4], [5].

FMCW radar is increasingly used in smart city systems, traffic monitoring, robotic navigation, healthcare monitoring, and contactless sensing. AI-enabled anomaly detection improves reliability in these applications by continuously analyzing radar signal behavior and identifying abnormal patterns. Integration with edge devices, cloud platforms, and intelligent dashboards can further support real-time monitoring and decision-making [6]–[9].

The significance of Hybrid Autoencoder-LSTM models lies in their ability to combine reconstruction-based anomaly scoring with sequential pattern analysis. This makes them useful for both immediate anomaly detection and long-term degradation monitoring. When combined with explainable AI and cybersecurity-aware detection, such frameworks can support safer and more trustworthy intelligent radar systems [10]–[12].

7. Research Gaps and Future Directions

Standardized evaluation protocols are also needed. Current studies often differ in dataset selection, preprocessing steps, anomaly definitions, train-test splitting, and reporting metrics, making direct comparison difficult. Future research should define benchmark datasets, common performance indicators, and reproducible experimental setups for FMCW radar anomaly detection. Such standardization will help researchers compare algorithms fairly and accelerate development of models suitable for real-world deployment.

Despite strong progress, several research gaps remain in AI-based FMCW radar anomaly detection. The first major gap is the limited availability of large-scale real-world radar datasets containing diverse anomaly categories. Many studies rely on synthetic, laboratory-generated, or controlled datasets that may not represent real operational complexity involving weather changes, dynamic objects, sensor aging, and electromagnetic interference [1], [2].

Class imbalance is another important issue because anomalous radar conditions occur far less frequently than normal operation. Models trained on imbalanced data may become biased toward normal classes and fail to detect rare but critical faults. Future work should explore data augmentation, synthetic anomaly generation, generative adversarial networks, adaptive sampling, and cost-sensitive learning to improve detection sensitivity [3].

Real-time deployment remains challenging because advanced deep learning models often require considerable computation and memory. Embedded radar systems, autonomous vehicles, unmanned aerial platforms, and industrial devices demand low-latency processing with limited resources. Lightweight neural architectures, pruning, quantization, model compression, hardware acceleration, and edge AI optimization should therefore be prioritized [4].

Interpretability is also essential in safety-critical radar applications. Black-box predictions may reduce trust among engineers and operators. Explainable AI techniques can help identify which signal regions or temporal patterns contributed to anomaly decisions. Such transparency can improve debugging, validation, and operational acceptance of intelligent radar monitoring systems [5].

Future research should integrate anomaly detection with predictive maintenance, fault diagnosis, cybersecurity monitoring, and decision-support systems. Current studies often focus on isolated detection tasks, while practical radar systems require unified frameworks capable of identifying degradation trends, classifying fault type, estimating severity, and recommending maintenance action [6], [7].

Multi-sensor fusion is another promising direction. Autonomous platforms often combine radar with LiDAR, cameras, ultrasonic sensors, GPS, and IoT devices. Integrating radar anomaly detection with other sensing modalities may improve environmental awareness and fault localization. Federated learning, transfer learning, domain adaptation, and self-supervised learning can also improve generalization across different operational domains [8]–[12].

Overall, future intelligent radar monitoring systems should be accurate, lightweight, explainable, adaptive, privacy-preserving, and cybersecurity-aware. Attention mechanisms, Transformer models, edge AI deployment, federated learning, and standardized benchmarking are expected to play important roles in improving next-generation FMCW radar anomaly detection frameworks.

8. CONCLUSION

In summary, the reviewed literature confirms that FMCW radar anomaly detection is not only a signal-processing problem but also a broader intelligent monitoring challenge. Effective solutions must combine data quality, robust model design, real-time inference, explainability, and system-level integration. Hybrid Autoencoder-LSTM frameworks represent an important step in this direction because they address both spatial and temporal characteristics of radar signals while supporting future extensions toward edge deployment and predictive maintenance.

This review presented a compact analysis of AI-based anomaly detection frameworks for FMCW radar systems. FMCW radar is widely used in autonomous vehicles, aerospace systems, industrial automation, healthcare monitoring, smart transportation, robotics, and defense applications because of its ability to provide reliable range estimation, velocity measurement, and real-time object detection. However, radar performance can be affected by hardware degradation, environmental interference, signal distortion, multipath propagation, calibration instability, and cybersecurity threats.

Traditional monitoring methods based on statistical analysis and fixed thresholds are limited in detecting subtle, evolving, and previously unseen anomalies. AI, ML, and DL techniques provide more adaptive solutions by learning complex spatial and temporal patterns from radar data. Among these methods, Autoencoders and LSTM networks are particularly important. Autoencoders learn normal signal representations and detect deviations using reconstruction error, while LSTM networks model temporal dependencies in sequential radar observations.
Hybrid Autoencoder-LSTM architectures offer strong potential because they combine spatial reconstruction learning with temporal sequence modeling. Comparative evidence indicates that these hybrid models generally outperform threshold-based methods, SVM, Random Forest, standalone Autoencoders, and standalone LSTM models in accuracy, robustness, and adaptability. They also support predictive maintenance by identifying early-stage degradation before complete system failure occurs.

The review also identified important limitations, including lack of diverse real-world datasets, class imbalance, computational complexity, deployment constraints, poor interpretability, environmental variability, and cybersecurity vulnerabilities. Future research should focus on lightweight edge AI models, explainable AI, attention-based architectures, federated learning, multi-sensor fusion, adaptive thresholding, and standardized benchmarking. Overall, AI-enabled Hybrid Autoencoder-LSTM frameworks provide a scalable and intelligent pathway for improving reliability, safety, and predictive maintenance in next-generation FMCW radar systems.

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