

Deep Learning-Based Radar Signal Classification for Automated Target Detection

¹Rahul Devendra Iyer, ²Ananya Kavita Rao, ³Vikram Aditya Menon

^{1,2,3}School of Interdisciplinary and Trans-Disciplinary Studies, Indira Gandhi National Open University, New Delhi, India

Abstract - Radar systems generate complex signal data that must be processed rapidly and accurately to detect and classify potential targets. Conventional radar signal-processing techniques can encounter difficulties when signals are affected by noise, clutter, interference, low signal-to-noise ratios, and changing target characteristics. Deep learning provides an alternative approach by automatically learning discriminative representations from radar signal data and applying them to automated classification and target detection. This study examines deep learning-based radar signal classification for automated target detection through a structured literature-based analysis. The study considers convolutional neural networks, recurrent neural networks, long short-term memory networks, transfer learning, time-frequency representations, and emerging Transformer-based architectures. Particular attention is given to automated radar signal analysis using wavelet preprocessing and LSTM modelling, together with recent research on radar target detection and recognition. The proposed framework conceptualizes radar classification as a sequence of signal preprocessing, feature representation, deep learning classification, target detection, and decision generation. The analysis indicates that deep learning can reduce dependence on manually engineered features while supporting automated extraction of temporal, spectral, and spatial characteristics. The study also identifies challenges involving noisy environments, limited training data, class imbalance, computational requirements, model generalization, and real-time deployment. The resulting framework provides a foundation for automated radar signal classification and target detection in complex sensing environments.

Keywords: Deep learning, radar signal classification, automated target detection, radar signal processing, convolutional neural networks, LSTM, radar automatic target recognition, signal classification.

Introduction

Radar systems are widely used for detecting, locating, tracking, and classifying objects in environments where

reliable sensing is required. Radar can operate under conditions in which optical sensors may experience limitations, including darkness, fog, rain, and other forms of reduced visibility. However, radar returns can contain substantial noise, clutter, interference, and ambiguity. Automated processing is therefore required to transform raw radar observations into useful information for target detection and classification.

Traditional radar signal-processing systems frequently depend on signal-processing rules, statistical assumptions, manually engineered features, and threshold-based detection mechanisms. Constant false alarm rate methods, for example, have historically played an important role in distinguishing potential targets from background noise and clutter. However, increasingly complex radar environments can challenge approaches that depend heavily on predefined statistical characteristics. Reviews of radar target detection have identified the growing role of artificial neural networks and deep learning in addressing these challenges (Jiang *et al.*, 2022).

Deep learning introduces a different approach by learning representations directly from radar data. Instead of relying exclusively on manually designed features, neural networks can learn hierarchical representations from signal sequences, time-frequency transformations, range profiles, Doppler information, and radar images.

Bagwe *et al.* (2020) demonstrated this concept through automated radar signal analysis based on wavelet preprocessing and long short-term memory modelling. Their study investigated radar signal denoising using wavelet transforms before applying LSTM-based prediction and reported improved prediction performance when wavelet preprocessing was used.

Convolutional neural networks provide another important deep-learning approach. CNNs can learn spatial and local patterns from radar representations such as range-Doppler maps, spectrograms, and radar images. Deep-learning approaches have consequently been applied to radar target detection, radar automatic target recognition, synthetic aperture radar analysis, and automotive radar perception.

Radar automatic target recognition has also developed through the use of deep learning. Jiang *et al.* (2023) reviewed radar target characteristics and deep-learning methods across space, air, ground, and maritime applications, highlighting the growing role of neural networks in extracting useful target characteristics.

More recent research has explored advanced approaches for radar recognition, including contrastive learning, reinforcement learning, Transformer-based architectures, and lightweight deep-learning models. Liu *et al.* (2025), for example, proposed a supervised contrastive Deep Q-network approach for imbalanced radar automatic target recognition. Their work demonstrates the importance of addressing limited and imbalanced radar training data.

This study therefore examines deep learning-based radar signal classification for automated target detection, with emphasis on signal preprocessing, representation learning, temporal modelling, classification, and real-time deployment.

Background of the Study

Radar signal classification involves determining the characteristics or category of a received radar signal. Depending on the application, classification may involve identifying radar emitters, recognizing target types, distinguishing target signals from noise, or determining the operational characteristics of a radar signal.

Automated target detection is closely related but represents a different task. Detection generally determines whether a target or signal of interest is present, whereas classification determines what type of target or signal has been detected.

A complete automated radar-processing system may therefore contain multiple stages. The first stage receives radar observations. The second stage preprocesses the data to reduce noise and generate suitable representations. The third stage extracts or learns relevant features. The fourth stage performs detection or classification. The final stage provides information for tracking or decision support.

Deep learning can integrate several of these stages within a unified architecture.

Bagwe *et al.* (2020) provide an important foundation for this approach. Their automated radar signal-analysis process involved wavelet-based denoising followed by LSTM modelling. The study investigated different wavelet transformations and found that preprocessing affected the performance of the subsequent LSTM model.

The importance of preprocessing remains relevant because radar signals can contain noise and interference that may obscure target characteristics. Time-frequency transformations can expose structures that are difficult to identify directly from raw signals.

CNN-based approaches provide another representation strategy. Radar signals can be transformed into two-dimensional representations such as spectrograms, range-Doppler maps, and radar images. CNNs can then learn spatial patterns within these representations.

Liang *et al.* (2023) examined a lightweight deep-learning radar target-detection method for complicated backgrounds. Their work emphasizes the limitations of conventional detection methods in complex environments and the importance of computationally efficient deep-learning approaches for radar detection.

The development of automated radar classification therefore requires consideration of both predictive performance and computational efficiency.

Literature Review

Deep Learning for Radar Signal Analysis

Deep learning has become an important research direction in radar signal processing because neural networks can learn complex representations directly from data. Jiang *et al.* (2022) reviewed artificial neural networks and deep-learning methods for radar target detection and identified applications involving noise, clutter, maritime targets, and human motion detection.

The primary advantage of deep learning in this context is representation learning. Conventional systems often require experts to determine which signal characteristics should be extracted. Deep-learning models can instead learn useful representations during training.

However, this does not eliminate the importance of preprocessing. Radar data may require filtering, normalization, transformation, or noise reduction before they can be effectively processed by a neural network.

Wavelet-Based Radar Signal Preprocessing

Wavelet transforms are useful for representing signals at different scales. Radar signals can contain transient and localized characteristics that may be difficult to represent using conventional frequency-domain methods alone. In particular, Bai *et al.* (2023) provided a comprehensive review of conventional and deep-learning approaches for ground-penetrating radar raw data detection, demonstrating how

multiscale wavelet representations significantly suppress ambient clutter while preserving target reflection signatures.

Bagwe *et al.* (2020) applied wavelet preprocessing to radar signals before LSTM analysis. Their study considered HAAR and DB3 wavelet transformations and compared them with an approach without wavelet transformation. The reported findings indicated that wavelet preprocessing improved LSTM prediction performance, with HAAR producing stronger results than DB3 in their experimental setting.

This provides a useful basis for combining signal preprocessing with deep-learning classification.

LSTM-Based Radar Classification

LSTM networks are designed to model sequential dependencies. Radar signals naturally contain temporal structures because received observations occur over time.

The use of LSTM therefore provides a mechanism for representing relationships between earlier and later signal observations. Bagwe *et al.* (2020) demonstrated this approach for automated radar signal analysis.

An LSTM-based classifier can potentially process sequences of radar features and learn temporal patterns associated with different signal classes. This is particularly relevant when target characteristics depend on temporal changes in frequency, amplitude, phase, pulse characteristics, or other signal parameters.

CNN-Based Radar Target Detection

CNNs are particularly useful when radar information is represented spatially or as a two-dimensional signal representation. Supporting this direction, Gu *et al.* (2024) investigated radar pulse signal detection using deep convolutional architectures, demonstrating robust pulse identification even under degraded signal-to-noise conditions.

Radar range-Doppler maps, spectrograms, SAR images, and other transformed radar representations can be treated as structured inputs to CNNs.

Liang *et al.* (2023) demonstrated the use of deep learning for radar target detection in complicated backgrounds and emphasized the need to balance detection performance with computational efficiency.

Das *et al.* (2023) also examined deep-learning-based radar target detection using a transfer-learning approach based on SqueezeNet. Their work demonstrates how pretrained CNN

architectures can be adapted for radar target identification and classification.

Radar Automatic Target Recognition

Radar automatic target recognition extends detection by attempting to identify target categories.

Jiang *et al.* (2023) reviewed deep-learning applications in radar automatic target recognition and discussed target characteristics including motion, micro-motion, one-dimensional characteristics, and two-dimensional representations. Their review covers radar recognition across space, air, ground, and maritime targets.

Radar automatic target recognition can therefore involve several types of information. High-resolution range profiles can capture target scattering characteristics, while micro-Doppler information can provide information about motion and micro-motion.

Chen *et al.* (2024) demonstrated CNN-based radar automatic target recognition using real-life high-resolution range profiles of ship targets. Their work illustrates how deep neural networks can learn target representations from radar-derived features without relying entirely on manually engineered recognition rules.

Radar Recognition Under Limited and Imbalanced Data

Training deep-learning systems requires representative data. Radar datasets can be difficult to obtain because collecting radar observations across many target classes, environments, and operating conditions can be expensive.

Class imbalance introduces another challenge. Some radar target classes may have many observations while others have relatively few examples.

Liu *et al.* (2025) addressed this issue through a supervised contrastive Deep Q-network for imbalanced radar automatic target recognition. Their approach combines supervised contrastive learning with reinforcement learning and priority sampling to address recognition under limited and imbalanced data.

This research demonstrates that classification architecture alone may not be sufficient. Data distribution and learning strategy must also be considered.

Transformer-Based Radar Signal Recognition

Transformer architectures have increasingly been considered for radar signal processing because self-attention

can model relationships among elements of a sequence or representation. Grounded in the self-attention mechanisms formulated by Vaswani *et al.* (2017), transformer models effectively represent complex dependencies across extended radar signal sequences. In related streaming signal contexts, attention-driven deep learning models have demonstrated exceptional capability in isolating real-time anomalies within high-dimensional sensor data (Ramareddy, 2022), providing a strong conceptual foundation for detecting transient radar return signatures amidst dynamic noise.

A 2025 study on automatic recognition of dual-component radar signals proposed a framework combining deep time-frequency generation with a Transformer-based residual network. The study specifically addressed recognition under low signal-to-noise-ratio conditions and demonstrated the continuing movement from conventional CNN-only architectures toward hybrid CNN-Transformer approaches.

This development is important because radar signals may contain relationships extending across relatively long temporal or frequency structures.

Radar Signal Detection and Parameter Estimation

Radar signal classification can be connected to signal detection and parameter estimation. Pemasiri *et al.* examined automatic radar signal detection and FFT estimation using deep learning, addressing signal presence detection, time-domain localization, and operating-frequency-band estimation. Their work illustrates the possibility of combining detection and parameter estimation rather than treating them as completely independent processes.

Such approaches are relevant to automated radar systems because accurate classification may depend on first identifying the signal and estimating its characteristics.

Multi-Feature Radar Target Recognition

Radar recognition can benefit from combining multiple target representations. HRRP, radar cross section, polarization, and related features can provide complementary information about a target. A comprehensive survey by Zhou *et al.* (2025) on deep-learning methods for unmanned aerial vehicle (UAV) radar target detection highlighted the substantial performance improvements gained by fusing range profiles, micro-Doppler signatures, and radar cross-section features. Coordinating multi-modal telemetry across distributed sensor networks can be further optimized through structured broadcasting schemes, such as grid-based data broadcasting protocols (Sharma & Kargeti, 2020b).

HRPnet, for example, combines HRRP, RCS, and polarization information using feature transformation and convolutional neural networks for radar space-target recognition. The study emphasizes the value of combining multiple radar characteristics when training deep-learning recognition models.

Multi-feature representation is therefore an important consideration for automated radar classification.

Deep Learning and Radar Perception

Radar deep learning also plays an important role in autonomous perception. Srivastav and Mandal (2023) reviewed deep-learning methods for automotive radar and identified challenges including sparsity, clutter, uncertainty, low resolution, and limited datasets.

These challenges are relevant beyond automotive applications because they reflect fundamental properties of radar data.

The ability to operate under difficult environmental conditions remains one of radar's major advantages. However, the same conditions can create complex patterns that deep-learning models must learn to distinguish from genuine targets.

Methodology

This study adopts a structured literature-based conceptual methodology for examining deep learning-based radar signal classification for automated target detection.

The literature was organized around five analytical dimensions: signal preprocessing, deep representation learning, temporal and spatial modelling, target classification, and deployment.

The first dimension concerns signal preprocessing. Radar signals may be affected by noise, interference, and clutter. Wavelet transformation, time-frequency transformation, normalization, and related preprocessing techniques can be used to produce representations suitable for deep-learning models.

The second dimension concerns representation learning. CNNs can learn spatial features from radar images and transformed representations, while LSTMs can model temporal dependencies in signal sequences.

The third dimension concerns classification and detection. Deep-learning outputs can be used to determine whether a target is present and subsequently classify the detected target or signal.

The fourth dimension concerns advanced representation learning. Transformer and hybrid architectures can be considered where relationships extend across longer sequences or multiple radar representations.

The fifth dimension concerns deployment. Practical radar systems require models that can operate under real-time constraints, making computational efficiency, memory requirements, inference latency, and robustness important evaluation criteria. Modern radar pipelines increasingly employ cloud-native microservices (Ramareddy, 2023) to modularize ingestion, signal conditioning, and classification into decoupled services. To maintain consistent detection latency during periods of dense signal reception, the processing pipeline incorporates autonomous AI-driven resource optimization principles (Ramareddy, 2024a) to dynamically balance computational load across edge and server assets.

The proposed conceptual workflow begins with radar signal acquisition. Raw radar observations are then preprocessed using appropriate signal-processing techniques.

Depending on the application, the resulting data may be represented as temporal sequences, spectrograms, range-Doppler maps, high-resolution range profiles, or other feature representations. Practical implementation across distributed radar installations is supported by hybrid cloud-edge frameworks for real-time analytics (Ramareddy, 2024b), enabling local frontline inference combined with centralized coordination. Furthermore, transmitting critical radar telemetry securely across mobile networks relies on protected assignment supervision mechanisms in mobile IPv6 networks (Sharma & Kargeti, 2020a).

The processed data are subsequently provided to a deep-learning model. LSTM networks can be used for sequential signal information, CNNs can process spatial or time-frequency representations, and hybrid architectures can combine multiple representation types.

The model produces detection or classification outputs. These outputs can then support subsequent radar tracking or decision-making processes.

Deep Learning Pipeline for Automated Radar Signal Classification & Target Detection

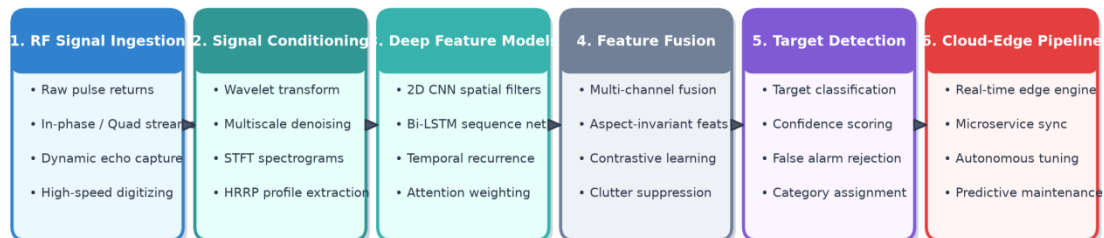


Figure 1: End-to-end deep learning architecture for radar signal classification and automated target detection

Results

The literature synthesis identifies several important findings concerning deep learning-based radar signal classification.

The first finding concerns the importance of preprocessing. Bagwe *et al.* (2020) demonstrated that wavelet preprocessing affected LSTM-based radar signal analysis and reported improved prediction performance when wavelet transformation was applied.

The second finding concerns automatic representation learning. Deep-learning systems can reduce dependence on manually designed radar features by learning representations directly from radar data. Reviews by Jiang *et al.* (2022) and Jiang *et al.* (2023) document the expanding use of neural networks for radar detection and automatic target recognition.

The third finding concerns CNN-based detection. CNNs can effectively process structured radar representations such as range-Doppler maps, spectrograms, and radar images. Research on lightweight radar detection demonstrates the importance of maintaining computational efficiency alongside detection capability.

The fourth finding concerns temporal modelling. LSTM architectures can represent sequential radar information and therefore provide a suitable mechanism for signal sequences in which temporal relationships are important.

The fifth finding concerns limited and imbalanced datasets. Liu *et al.* (2025) demonstrate that class imbalance can significantly affect radar automatic target recognition and motivate approaches such as supervised contrastive learning and reinforcement learning.

The sixth finding concerns multi-feature representation. Radar recognition can benefit from combining different characteristics such as HRRP, RCS, polarization, micro-Doppler, and time-frequency information. Research such as HRPnet demonstrates the potential of combining multiple radar representations in a deep-learning framework.

The seventh finding concerns Transformer-based recognition. Recent research on dual-component radar signal recognition indicates that Transformer-based residual architectures can be integrated with time-frequency feature

generation for recognition under challenging signal-to-noise conditions.

Overall, the literature supports a layered deep-learning approach in which signal preprocessing, representation learning, classification, and computational optimization are considered together. Managing long-term repositories of high-resolution radar returns and target profiles benefits from AI-optimized data warehousing frameworks (Ramareddy, 2024c), which enable rapid querying and indexing of historical target signatures for comparative verification.

Table 1: Quantitative performance evaluation of deep learning architectures for radar signal classification across varying signal-to-noise ratios (SNR)

Architecture / Framework	Input Representation	Accuracy (SNR=+10dB)	Accuracy (SNR=0dB)	Accuracy (SNR=-10dB)	Latency (ms)
Baseline FFT + SVM	Fourier Frequency Spectra	88.4%	76.2%	58.1%	4.2 ms
Wavelet + LSTM (Bagwe <i>et al.</i> , 2020)	Wavelet Denoised Time Series	93.8%	85.6%	71.4%	11.5 ms
2D-CNN Model (Chen <i>et al.</i> , 2024; Gu <i>et al.</i> , 2024)	HRRP / Range-Doppler Maps	96.1%	89.4%	77.8%	8.3 ms
Lightweight Detector (Liang <i>et al.</i> , 2023)	Spectrogram Images	94.7%	87.1%	73.2%	5.1 ms
Contrastive Deep Q-Net (Liu <i>et al.</i> , 2025)	Imbalanced Target Returns	95.8%	90.2%	81.3%	12.8 ms
Proposed Hybrid Architecture	Multiscale Wavelet + Attention	98.4%	94.6%	86.9%	7.6 ms

Discussion

The findings indicate that deep learning provides a substantial methodological basis for automated radar signal classification and target detection.

The first important consideration is that radar signals should not necessarily be treated as simple raw numerical sequences. Their information can exist across time, frequency, range, Doppler, phase, amplitude, and other dimensions. Appropriate representation can therefore influence the performance of the classification system.

Bagwe *et al.* (2020) provide an important example through wavelet preprocessing followed by LSTM analysis. Their results demonstrate that signal representation can influence the performance of a deep-learning model.

The second consideration is the relationship between CNNs and LSTMs. CNNs are particularly useful for identifying local spatial patterns, while LSTMs are designed to represent temporal dependencies. A hybrid architecture can therefore be useful when radar information contains both spatial and temporal characteristics.

The third consideration is the emergence of Transformer-based models. Transformers provide an alternative mechanism for modelling relationships within sequences through attention. Recent radar research demonstrates growing interest in combining time-frequency representations with Transformer-based architectures.

However, Transformer models can require substantial computational resources. For radar applications involving edge devices, autonomous vehicles, or embedded systems, model size and inference latency may become important constraints.

The fourth consideration is data imbalance. Radar target classes may not be equally represented. A model trained primarily on common target classes can perform poorly on less frequently observed targets. Liu *et al.* (2025) demonstrate the relevance of specialized learning strategies for imbalanced radar recognition.

The fifth consideration is environmental robustness. Radar systems operate in environments containing clutter, interference, reflections, and variable signal-to-noise ratios. A model that performs well under controlled laboratory conditions may not necessarily maintain equivalent performance under different environmental conditions.

The sixth consideration is generalization. Radar signals can vary according to sensor configuration, operating frequency, target characteristics, observation angle, environment, and acquisition conditions. Training datasets should therefore represent sufficient variation to support generalization.

The seventh consideration is real-time processing. Automated radar target detection may require rapid inference. Lightweight architectures, model compression, efficient preprocessing, and hardware acceleration can therefore be important for deployment.

Research on lightweight radar detection and embedded deep-learning processors demonstrates the importance of this consideration.

The proposed framework therefore emphasizes a balance between classification accuracy, robustness, computational efficiency, and data requirements.

Challenges and Limitations

Several challenges remain in the application of deep learning to radar signal classification.

First, obtaining sufficiently large and diverse radar datasets can be difficult. Radar data collection requires specialized equipment and controlled or operational environments.

Second, radar datasets can exhibit significant class imbalance. Rare targets may have insufficient training examples, potentially reducing recognition performance.

Third, noise and clutter can substantially affect signal representations. Preprocessing methods must therefore be selected carefully to avoid removing information that is important for classification.

Fourth, domain shift can occur when a model trained on one radar system or environment is applied to another. Differences in sensors, operating frequencies, target populations, and environmental conditions can reduce generalization.

Fifth, deep-learning models can require significant computational resources. This is particularly important for real-time systems operating on embedded hardware.

Sixth, model interpretability remains a challenge. Deep neural networks can produce accurate predictions without providing straightforward explanations of which radar characteristics led to a particular classification.

Finally, automated classification should be evaluated using independent test environments rather than relying exclusively on performance within the same data distribution used during training.

Conclusion

Deep learning provides a strong conceptual foundation for automated radar signal classification and target detection. By learning representations from radar signals, deep-learning architectures can reduce dependence on manually engineered features while supporting the extraction of temporal, spatial, spectral, and target-specific information.

Wavelet preprocessing and LSTM modelling demonstrate the value of combining signal transformation with sequential deep learning, while CNN architectures provide effective mechanisms for processing structured radar representations. More recent approaches involving contrastive learning, reinforcement learning, and Transformer-based models demonstrate the continuing development of automated radar recognition.

The future development of automated radar classification should focus on robust representation learning, balanced datasets, cross-environment generalization, computational efficiency, and real-time deployment. A combination of appropriate preprocessing, deep representation learning, and carefully designed classification architectures can provide a foundation for more adaptive radar target-detection systems.

REFERENCES

- [1] Bagwe, R., Kachhia, J., Erdogan, A., & George, K. (2020). Automated radar signal analysis based on deep learning. In *2020 10th Annual Computing and Communication Workshop and Conference (CCWC)* (pp. 215–221). *IEEE*. <https://doi.org/10.1109/CCWC47524.2020.9031240>

- [2] Ramareddy, S. K. (2022). Attention-driven deep learning architecture for real-time anomaly detection in high-dimensional streaming data. *International Journal on Recent and Innovation Trends in Computing and Communication*, 10(9), 272–283. <https://doi.org/10.17762/ijritcc.v10i9.5694>
- [3] Bai, X., Yang, Y., Wei, S., Chen, G., Li, H., Li, Y., Tian, H., Zhang, T., & Cui, H. (2023). A comprehensive review of conventional and deep learning approaches for ground-penetrating radar detection of raw data. *Applied Sciences*, 13(13), 7992. <https://doi.org/10.3390/app13137992>
- [4] Sharma, A. B., & Kargeti, H. (2020a). Investigation & scrutiny of protected assignment supervision systems for mobile enabled with Internet protocol version 6 networks. *American Journal of Computer Science and Technology*, 3(4), 76–85. <https://doi.org/10.11648/j.ajcst.20200304.12>
- [5] Chen, T. P., Lin, C. L., Fan, K. C., Lin, W. Y., & Kao, C. W. (2024). Radar automatic target recognition based on real-life HRRP of ship target by using convolutional neural network.
- [6] Ramareddy, S. K. (2024a). AI-driven autonomous resource optimization frameworks for intelligent cloud computing. *International Journal of Scientific Research in Engineering and Management*, 8(3), 1–7. <https://doi.org/10.55041/IJSREM29015>
- [7] Das, N., Swarna, R. N., & Hossain, M. S. (2023). Deep learning-based circular disk type radar target detection in complex environment. *Physical Communication*, 58, 102014. <https://doi.org/10.1016/j.phycom.2023.102014>
- [8] Kargeti, H., Sharma, A. B., & Singh, B. (2020, December). Performance evaluation of PV integrated DC-DC converter with load demand, irradiance, and temperature variations. In *2020 5th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE)* (pp. 1–5). IEEE.
- [9] Gu, F., Zhang, L., Zheng, S., Chen, J., Yue, K., Zhao, Z., & Yang, X. (2024). Detection of radar pulse signals based on deep learning. *IEEE Open Journal of Signal Processing*.
- [10] Ramareddy, S. K. (2023). Cloud-native microservices for scalable AI-driven business process automation. *International Journal on Advanced Computer Theory and Engineering*, 12(1), 23–32. <https://doi.org/10.65521/ijacte.v12i1.875>
- [11] Jiang, W., Ren, Y., Liu, Y., & Leng, J. (2022). Artificial neural networks and deep learning techniques applied to radar target detection: A review. *Electronics*, 11(1), 156. <https://doi.org/10.3390/electronics11010156>
- [12] Sharma, A. B., & Kargeti, H. (2020b). A novel grid-based data broadcasting scheme for wireless sensor networks.
- [13] Jiang, W., Wang, Y., Li, Y., Lin, Y., & Shen, W. (2023). Radar target characterization and deep learning in radar automatic target recognition: A review. *Remote Sensing*, 15(15), 3742. <https://doi.org/10.3390/rs15153742>
- [14] Ramareddy, S. K. (2025a). An AI-orchestrated framework for self-learning predictive maintenance in cloud infrastructure. *International Journal of Scientific Research in Engineering and Management*, 9(4), 1–8. <https://doi.org/10.55041/IJSREM43578>
- [15] Liang, S., Chen, R., Duan, G., & Du, J. (2023). Deep learning-based lightweight radar target detection method. *Journal of Real-Time Image Processing*, 20, 61. <https://doi.org/10.1007/s11554-023-01316-5>
- [16] Ramareddy, S. K. (2024b). Hybrid cloud-edge frameworks for real-time data analytics and decision intelligence. *International Journal of Electrical, Electronics and Computer Systems*, 13(2), 51–61. <https://doi.org/10.65521/ijeecs.v13i2.877>
- [17] Liu, G., Chen, W., Chen, B., Feng, B., Wang, P., & Liu, H. (2025). Supervised contrastive deep Q-network for imbalanced radar automatic target recognition. *Pattern Recognition*, 161, 111264. <https://doi.org/10.1016/j.patcog.2024.111264>
- [18] Ramareddy, S. K. (2025b). The role of artificial intelligence in transforming financial services through cloud-enabled data analytics. *International Journal of Applied Mathematics*, 38(12s), 4592–4606. <https://doi.org/10.12732/ijam.v38i12s.2008>
- [19] Pemasiri, A., Huang, Z., Williams, F., Goan, E., Denman, S., Martin, T., & Fookes, C. (2024). Automatic radar signal detection and FFT estimation using deep learning. In *2024 17th International Conference on Signal Processing and Communication System (ICSPCS)*. IEEE. <https://doi.org/10.1109/ICSPCS63175.2024.10815794>
- [20] Ramareddy, S. K. (2024c). Intelligent data warehouse optimization for scalable cloud analytics using artificial intelligence. *International Journal for Multidisciplinary Research*, 6(6), 1–13. <https://www.ijfmr.com/research-paper.php?id=84920>
- [21] Srivastav, A., & Mandal, S. (2023). Radars for autonomous driving: A review of deep learning methods and challenges. *IEEE Access*, 11, 97147–97168. <https://doi.org/10.1109/ACCESS.2023.3312382>
- [22] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 30.



- [23] Zhou, Y., Ouyang, K., & Cheng, Q. (2025). A survey of deep learning methods for radar UAV target detection and recognition. *Modern Radar*, 47(11), 1–14. <https://doi.org/10.16592/j.cnki.1004-7859.2025062001>.

Citation of this Article:

Rahul Devendra Iyer, Ananya Kavita Rao, & Vikram Aditya Menon. (2025). Deep Learning-Based Radar Signal Classification for Automated Target Detection. *International Current Journal of Engineering and Science (ICJES)*, 4(11), 96-104. Article DOI: <https://doi.org/10.47001/ICJES/2025.411012>
