Textile & Leather Review

ISSN 2623-6281 | www.tlr-journal.com | 10.31881/TLR

Radar Signal Target Detection and Threat Level Assessment Based on CNN

Tianyi Chen

How to cite: Chen T. Radar Signal Target Detection and Threat Level Assessment Based on CNN. Textile & Leather Review. 2026; 9:2299-2324. https://doi.org/10.31881/TLR.2026.2299

How to link: https://doi.org/10.31881/TLR.2026.2299

Published: 25 April 2026

Radar Signal Target Detection and Threat Level Assessment Based on CNN

Tianyi Chen

School of Electronic Information, Wuhan University, Wuhan 430072, China
cty1454343290cty@163.com

Article
https://doi.org/10.31881/TLR.2026.2299
Published 25 April 2026

ABSTRACT

The modern electromagnetic environment is becoming increasingly complex. Traditional radar signal processing methods have significant limitations in dealing with strong clutter interference and stealth target detection, failing to meet the accuracy and timeliness requirements of military reconnaissance and defense systems for target identification. This research aims to construct a radar signal target detection and threat level evaluation system based on convolutional neural networks (CNNs) to achieve accurate target detection and threat assessment in complex environments. Methodologically, the CNN network architecture is first optimized (including hierarchical design, activation function selection, and optimization algorithm adaptation). Then, a diversified dataset covering simulation, experimental, and publicly available data is constructed, and data augmentation techniques are used to expand the sample. Simultaneously, a five-level threat evaluation index system based on carrier frequency, pulse width, and repetition rate is established, and a combined weighting method is used to improve the objectivity of the evaluation. Experimental results show that the proposed model achieves a Target Detection Accuracy (TDA) of 89.2%, a threat level evaluation accuracy of 87.6%, and a processing speed of 32.8 FPS, significantly outperforming traditional methods and classic CNN models. Furthermore, it exhibits good robustness in complex electromagnetic environments. This research provides an effective technical path for the intelligent upgrading of radar systems and can provide accurate threat assessment support for military decision-making, possessing significant engineering application value.

KEYWORDS
CNN, radar signal, target detection, threat level, deep learning

INTRODUCTION

The rapid development of contemporary radar technology has driven the modernization of military reconnaissance and defense systems. Radar signal target detection, as a core technology in modern warfare, serves as the fundamental prerequisite for tactical situational awareness of operational decisions. The modern electromagnetic environment is becoming increasingly complex, and radar systems face severe challenges such as limited spectrum resources and continuous innovation in jamming technology[1]. Traditional radar signal processing methods have significant limitations in dealing with complex sea surface environments, strong clutter interference, and stealth target detection. Sea surface target range detection faces numerous challenges such as waves, sea fog, and changes in sea state. Background interference such as sea clutter causes target echo signals to mix with background clutter, significantly increasing the uncertainty of target detection[2].

The rapid development of deep learning technology, especially convolutional neural networks (CNN), has brought new breakthrough opportunities to radar signal processing. CNN's powerful feature extraction capabilities and pattern recognition advantages in image recognition provide an effective way to solve complex electromagnetic scattering phenomena and radar cross-section (RCS) fluctuations and multipath interference[3]. As a key technology of radar electronic warfare systems, radar radiation source signal identification faces challenges such as complex signal forms, soaring signal density, and large signal-to-noise ratio variations, placing higher demands on the intelligence, automation, accuracy, and timeliness of the identification system[4].

Threat level assessment, as an important component of radar system intelligence, can effectively improve the radar's ability to identify and warn of threatening targets. By constructing a radar signal target detection model based on CNN and combining it with a threat level assessment system, accurate prediction of radar threat levels can be achieved[5]. This technological fusion not only improves the target detection performance of radar systems in complex electromagnetic environments but also provides more accurate threat assessment information for military decision-making, possessing significant theoretical value and practical application significance.

In recent years, radar signal target detection technology based on deep learning has developed rapidly, and the application of convolutional neural networks in the field of radar target recognition has become increasingly mature. Foreign scholars started earlier in deep learning methods for radar signal processing, achieving automatic feature extraction of complex radar signals by constructing multi-layer network structures. Related research uses deep CNNs to automatically extract features from target HRRPs, fuses the recognition results of various radar HRRPs, and determines whether the target is known by comparing the highest global target probability with a preset threshold[6].

Domestic researchers, based on fully considering the time-shift sensitivity, target azimuth sensitivity, and high redundancy of radar HRRP data, have proposed a new CNN network structure for target recognition. This type of network uses large convolutional kernels, large stride convolutional layers, and large-grid max pooling, and uses a central loss function to correct the softmax loss function, thereby making the network more robust. Meanwhile, a method based on bispectral features and deep convolutional neural networks was also proposed. Experimental verification was conducted using measured satellite target data, and the network training demonstrated accurate and effective identification of radar targets[7].

In terms of model complexity and recognition accuracy, researchers used a simple 5-layer CNN neural network model to achieve effective identification of various radar signals, while deep models such as AlexNet, GoogLeNet, and ResNet50 showed higher recognition rates and better robustness in the identification of multiple types of radar radiation source signals. The radar signal identification method using extended residual networks (DRN) employs a 12-layer DRN model, achieving high recognition results and providing a new technical path for target detection in complex radar environments.

THEORETICAL BASIS

Basic Principles of CNN

Convolutional Neural Networks (CNN), as one of the core technologies in the field of deep learning, exhibits powerful feature extraction and pattern recognition capabilities in radar signal target detection. The basic architecture of CNN consists of an input layer, a sampling layer, a convolutional layer, an output layer, and a fully connected layer. Its training method uses the backpropagation algorithm[8]. In radar signal processing applications, CNNs can effectively process data with spatial structure, such as the time-domain and frequency-domain information[9]of complex-valued IQ signals.

The core of CNNs lies in convolution operations, where convolution kernels slide across the input data to extract local features. In a convolutional layer, each neuron in the output feature plane is connected at its input, and the weights of its connections are added to the local input weights, which are then added to the bias value. This design allows CNNs to capture the spatial dependencies of data, making them particularly suitable for processing radar time-frequency image recognition tasks. The weight-sharing mechanism not only reduces the number of network parameters but also enhances the model's translation invariance, which is crucial for detecting changes in target position in radar signals.

The training process of CNN networks is based on backpropagation and gradient descent optimization. Let the output feature map of the convolutional layer be:

$$F_{i,j} = \sigma\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} w_{m,n} \cdot x_{i+m,j+n} + b\right) \tag{1}$$

Where, $F_{i,j}$ represents the value of the output feature map at position (i, j) , $w_{m,n}$ is the convolution kernel weight, $x_{i+m,j+n}$ is the input data, b is the bias term, σ is the activation function.

In radar signal processing, CNNs, through multi-layer convolution and pooling operations, can extract feature representations from the original signal layer by layer from low to high levels, providing a solid technical foundation for subsequent target detection and threat level assessment.

Radar Signal Processing Methods

Radar signal processing, as a core technology of radar systems, is responsible for detecting and analyzing received echo signals, providing crucial support for the development of radar system functions from early ranging to more diversified approaches[10]. Radar signal processing methods also exhibit significant differences depending on the target and environmental conditions. Driven by both military needs and information technology, radar signal processing technology is undergoing profound changes, interacting with radar systems and increasingly demonstrating new technical characteristics.

Traditional radar signal processing methods mainly include linear regression, Butterworth low-pass filtering, and zero-phase-shift filtering[11]. Linear regression-based methods can effectively identify and remove anomalous data that significantly deviates from the overall trend, while simultaneously compensating for the data to ensure the overall trend and characteristics are preserved. Butterworth low-pass filters excel at removing high-frequency noise from signals, making curves smooth and glitch-free; however, this method may lead to lag in the results and potential disturbances at the beginning. Zero-phase-shift filtering, while addressing high-frequency noise interference, also suppresses waveform and signal peaks.

With the continuous development of modern radar signal processing technology, the segmented filtering method combines the advantages of low-pass filtering and linear regression. It segments the data, using linear regression for the peak portion and low-pass filtering for the rest, effectively preserving the radar peak value, which is beneficial for subsequent target velocity calculation. For applications such as automotive collision avoidance radar, signal processing algorithms need to preprocess the raw radar data, including filtering and noise reduction to improve signal quality. Then, appropriate signal processing algorithms such as FFT and CFAR are used for target detection and distance estimation[12].

APPLICATION OF CNN IN RADAR SIGNAL TARGET DETECTION

CNN Model Structure Selection

Network Hierarchical Design

The hierarchical structure design of convolutional neural networks in radar signal target detection tasks directly affects the feature extraction effect and detection accuracy. Traditional CNNs gradually increase the receptive field of the model by stacking convolutional layers to detect the entire signal [13-15]. Simultaneously, feature maps with different receptive fields can achieve the detection of targets at different scales. The network design of a radar signal target detection system needs to fully consider the time-frequency characteristics of the signal and the multi-scale variation law of the target.

The shallow layers of the network are mainly responsible for extracting basic features of radar signals, including low-level features such as frequency distribution, amplitude variation, and phase information. These layers typically use small convolutional kernel sizes, such as 3×3 or 5×5, which can capture local patterns and subtle changes in the signal. Intermediate layers gradually integrate low-level features to form more abstract representations by increasing the number of channels and the receptive field. Deep network structures are specifically designed to extract high-level semantic features, capable of recognizing complex target patterns and combinations of threat features [16]. The advantage of CNNs lies in their series of invariant interest points and pixel-to-global detection characteristics, making them particularly suitable for target detection tasks in radar signals.

To optimize the network hierarchical design, this study adopts a multi-branch parallel structure to process different types of radar signal features. By designing specialized skip connections and residual modules, the network can effectively alleviate the gradient vanishing problem and improve training efficiency. The mathematical expression of the network layers can be described as a progressive process of feature extraction:

$$F_l = \sigma(W_l * F_{l-1} + b_l) \tag{2}$$

Where F_l represents the feature mapping of the l layer, $W_l\ and\ b_l$ are the weights and bias parameters respectively, σ is the activation function, $*$ represents the convolution operation.

Selection of Activation Function

In the application of CNN models for radar signal target detection, the choice of activation function has a significant impact on model performance. The main role of activation functions is to introduce nonlinear factors, improve the neural network's expressive ability, and solve the problem of insufficient expressive and classification capabilities of linear models [17,18]. By introducing activation functions, CNNs can learn more complex feature representations, thereby improving the model's expressive ability and classification performance.

Considering the specific characteristics of radar signal target detection, this study compares and analyzes the performance of various activation functions in CNN models. Commonly used activation functions include ReLU, Sigmoid, Tanh, and LeakyReLU (table 1). ReLU has the advantages of simple computation and fast training convergence, but its derivative is 0 when the input value is negative, which may lead to the "death" of neurons. To solve this problem, LeakyReLU introduces a small slope in the negative region to avoid the gradient vanishing problem. Sigmoid maps input values to between 0 and 1 and is mainly used for probability prediction in binary classification tasks.

Table 1. Mathematical Expression of Activation Function

Activation Function	Mathematical Expression		Advantages	Disadvantages	Applicable Scenarios
ReLU	$f(x) = \max(0, x)$	(3)	Simple calculation, fast convergence	Derivative is 0 in negative regions	Hidden layer activation
LeakyReLU	$f(x) = \max(\alpha x, x)$	(4)	Avoid neuron death	Parameters need adjustment	Deep networks
Sigmoid	$f(x) = \frac{1}{1 + e^{-x}}$	(5)	Output probability distribution	Vanishing gradient	Binary classification output
Tanh	$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	(6)	Zero-mean output	Vanishing gradient	Regression task

Experimental results show that ReLU and ELU activation functions perform well in processing radar signal data. This study compared the performance of different activation functions on the training and test sets and finally selected a suitable combination of activation functions for radar signal feature extraction, laying the foundation for subsequent target detection and threat level assessment.

Comparison of Optimization Algorithms

In CNN radar signal target detection models, the choice of optimization algorithm directly affects the network's convergence speed and final performance. By comparing and analyzing the characteristics of different optimization algorithms in radar signal processing, a more scientific parameter adjustment strategy can be provided for model training [19]. This study focuses on comparing the performance differences of gradient descent, Adam optimizer, and RMSprop algorithm in radar target recognition tasks.

Gradient descent, as the most basic optimization algorithm, exhibits stable convergence characteristics when processing radar signal features, but its convergence speed is relatively slow. Adam optimizer combines the advantages of momentum method and adaptive learning rate, showing a faster convergence speed when processing complex radar signal patterns. RMSprop algorithm, by adaptively adjusting the learning rate, can maintain good stability when facing radar signals with different signal-to-noise ratios [20,21]. Experiments show that compressed residual network combined with appropriate optimization algorithm can achieve an average recognition rate of up to 95% for 14 radar radiation source signals under a signal-to-noise ratio of −14dB, with a running time reduction of about 88% compared to standard CNN.

The comparison of recognition accuracy among different optimization algorithms is shown in Table 2.

Table 2. Comparison of Recognition Accuracy of Different Optimization Algorithms

Optimization Algorithm	Convergence Speed	Memory Usage	Recognition Accuracy (%)	Applicable Scenarios
Gradient Descent Method	slow	low	87.3	Simple Signal Patterns
Adam	fast	Medium	93.8	Complex and Variable Signals
RMSprop	Medium	low	91.2	Low Signal-to-Noise Ratio Environments
AdaGrad	slow	Medium	89.6	Sparse Feature Signals

The evaluation of algorithm performance should not only consider convergence efficiency, but also focus on robustness performance in practical radar applications. By introducing improvements to the loss function, such as modifying the softmax loss function with a center loss function, the network can obtain features with smaller intra-class distances, thereby improving the overall recognition performance. The application of machine learning algorithms in radar signal processing is receiving increasing attention. By training models, different types of interference signals can be automatically learned and identified.

Dataset Construction and Preprocessing

Data Acquisition Approach

Data acquisition for radar signal target detection is a crucial step in building high-quality CNN models. Traditional military weapon systems typically identify target attributes using acquired radar track data. However, the target attribute identification performance of a single radar sensor is often affected by environmental noise and sensor-specific factors. Therefore, establishing a diversified data acquisition system is essential for improving detection accuracy.

In practical applications, radar data acquisition mainly includes three methods: laboratory simulation data, field measurement data, and publicly available datasets. Simulation data generated by the FMCW radar system in a laboratory environment has the advantages of controllable parameters and adjustable noise environment, providing an ideal testing platform for algorithm verification [22]. Acquiring field measurement data requires comprehensive consideration of sensor selection, data acquisition platform construction, and other factors. During data acquisition, it is necessary to ensure the spatiotemporal synchronization of sensor data to avoid data distortion due to timestamp offsets or inconsistent spatial coordinates. Different edge detection operators are used to perform edge detection processing on the original radar image, and then the CNN algorithm is used to predict the target size in the radar data.

The data acquisition process follows a two-stage processing model, including a data review stage and a formal information processing stage [23-24]. Regarding data quality assessment, quantitative indicators designed using objective data can all obtain the true values of the indicators, reflecting the quality gap between different threat intelligence sources in numerical form. Radar data processing technology mainly completes target position observation, target position extrapolation, and target position filtering. Through point-to-point correlation, target tracking detection, filtering, smoothing, and extrapolation, it effectively suppresses measurement errors while accurately estimating the target position and predicting the target position for the next moment.

Data Labeling Method

Data annotation methods for radar signal target detection are a crucial step in ensuring the training quality of CNN models, directly affecting the model's recognition accuracy and the accuracy of threat level assessment. In the field of radar signal processing, data annotation needs to consider multiple factors such as the frequency domain characteristics, time domain characteristics, and physical attributes of the target.

A hierarchical annotation strategy is adopted for processing different types of radar data. For high-resolution range profile (HRRP) data, annotators need to accurately label the target based on its geometric structure and scattering characteristics. The annotation of bispectral feature data focuses on the nonlinear coupling characteristics of the signal, determining the target category through spectral analysis. The annotation of track data involves the target's motion trajectory characteristics, including key parameters such as velocity, acceleration, and azimuth information.

Threat level labeling employs a multi-dimensional evaluation method, primarily considering three core indicators: carrier frequency, pulse width, and repetition rate. Higher carrier frequency indicates higher detection accuracy and a corresponding increase in threat level; narrower pulse width means lower radar resolution, improved accuracy, and increased threat level; a higher pulse repetition rate usually indicates that an enemy target has approached or been locked onto, significantly increasing the threat level.

$$T_{level} = \omega_1 \cdot f_{carrier} + \omega_2 \cdot \frac{1}{\tau_{pulse}} + \omega_3 \cdot f_{rep} \tag{3}$$

It should be noted that the linear weighted evaluation model (Equation 3) used in this study is primarily designed for conventional pulse radar parameters. When dealing with modern radars featuring low probability of interception (LPI) characteristics—which may employ wide pulses combined with pulse compression techniques—a simple inverse pulse width term may not fully account for their complex operating modes. Future versions will consider introducing nonlinear weighting coefficients based on fuzzy logic to more accurately characterize the dynamic contribution of radar operating modes to the threat level.

In the above formula, T_{level} represents the threat level score, and ω_1 、ω_2 、ω_3 are the weighting coefficients for carrier frequency, reciprocal of pulse width, and repetition rate, respectively. Based on these assessment criteria, this paper establishes a five-level threat level labeling system (table 3).

Table 3. Threat Level Labeling System

Threat Level	Carrier frequency range (GHz)	Pulse width range (μs)	Repetition rate range (kHz)	Threat Description
Level 1	2-4	10-50	1-5	Low Threat
Level 2	4-6	5-10	5-15	Lower Threat
Level 3	6-8	1-5	15-30	Medium Threat

Table 3. Threat Level Labeling System

Threat Level	Carrier frequency range (GHz)	Pulse width range (μs)	Repetition rate range (kHz)	Threat Description
Level 4	8-12	0.5-1	30-50	High Threat
Level 5	>12	<0.5	>50	Extremely High Threat

Labeling quality control ensures accuracy through multiple rounds of cross-validation, employs an expert review mechanism for secondary confirmation of labeling results, and establishes a labeling consistency verification process.

Data Augmentation Technology

In deep learning applications of radar target detection, data augmentation technology has become a key means to improve model performance and robustness. Due to the relatively small size of real radar datasets, various data augmentation methods can effectively expand training samples and improve the model's generalization ability.

Traditional geometric transformation enhancement methods demonstrate good adaptability in radar signal processing. Rotation transformation can simulate the radar echo characteristics of a target at different observation angles, effectively solving the rotation sensitivity problem in target recognition of aerial infrared images. Translation and scaling operations can simulate the changes in echo signals of a target at different distances and positions. The mathematical expressions for these transformations can be represented as:

$$T(x,y) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix} \tag{4}$$

Where θ where represents the rotation angle, \$(t_{x},t_{y})\$where is the translation vector.

Given the special characteristics of radar signals, frequency domain enhancement technology is particularly important. By adjusting the amplitude and phase of different frequency components, the signal characteristics under different weather conditions and electromagnetic environments can be simulated. The multi-dimensional scale feature enhancement method proposed by Du Yuchuan et al. utilizes a two-dimensional Gabor filter kernel function to enhance the features of target signals, providing an effective data augmentation strategy for weak radar targets.

In practical applications, the selection of data augmentation parameters has a decisive impact on the final effect. Studies have shown that the best enhancement effect can be obtained when the rotation angle is controlled within ±30° and the noise intensity ratio is kept between 0.1 and 0.3. Excessive enhancement operations may introduce too much interference, which may damage the model performance. This requires maintaining a moderate approach in the design of data augmentation strategies.

CONSTRUCTION OF THREAT LEVEL ASSESSMENT MODEL

Design of Evaluation Index System

Threat Level Classification Standards

Establishing threat level classification standards is the core foundation for assessing the threat level of radar signal targets, requiring comprehensive consideration of multiple dimensions of threat factors. Based on the characteristics of the radar system and actual application requirements, threat level assessment is mainly based on a comprehensive evaluation of the three key radiation source indicators: radar carrier frequency, pulse width, and repetition rate. Threat level assessment requires the adoption of protection criteria, that is, assessment through the protection of the protected object against attacks, which considers technical and operational protection measures within the information boundary.

In a specific threat level classification system, the threat level of radar targets is usually divided into five levels: extremely high threat, high threat, medium threat, low threat, and extremely low threat (table 4). This classification standard can effectively quantify the probability of a threat scenario leading to a threat state, providing a scientific basis for subsequent decision-making. The threat level calculation formula adopts a multi-attribute fusion approach, combining carrier frequency threat level T_f , pulse width threat level T_w , and repetition rate threat level T_r , and obtains the comprehensive threat level through weighted summation:

$$T_{total} = w_f \cdot T_f + w_w \cdot T_w + w_r \cdot T_r \tag{5}$$

Where w_f 、 w_w 、 w_r are the weight coefficients of each threat factor, and sat is fy $w_f + w_w + w_r = 1$

Table 4. Threat Level Classification Criteria

Threat Level	Threat Range	Carrier Frequency Characteristics	Pulse Width Characteristics	Repetition Rate Characteristics	Response Strategy
Extremely High Threat	0.8-1.0	Enemy Main Combat Frequency Band	Narrow Pulse High Precision	High Repetition Rate Tracking	Immediate Avoidance

Table 4. Threat Level Classification Criteria

Threat Level	Threat Range	Carrier Frequency Characteristics	Pulse Width Characteristics	Repetition Rate Characteristics	Response Strategy
High Threat	0.6-0.8	Threat Frequency Band Edge	Medium Pulse Width	Medium-High Repetition Rate	Active Jamming
Medium Threat	0.4-0.6	General Detection Band	Standard Pulse Width	Standard Repetition Rate	Continuous Monitoring
Low Threat	0.2-0.4	Civilian Band	Wide Pulse	Low Repetition Rate Scan	Routine Observation
Extremely Low Threat	0.0-0.2	Non-Threat Band	Ultra-Wide Pulse	Extremely Low Repetition Rate	Ignore

By establishing such a classification standard, a clear labeling system can be provided for the training of CNN models, enabling deep learning algorithms to accurately learn the feature patterns of different threat levels. This standardized threat level classification method not only improves the objectivity and consistency of the assessment but also lays the theoretical foundation for automated threat identification systems.

Selection of Assessment Method

In radar target threat assessment research, the selection of assessment method directly affects the accuracy and reliability of threat level determination. The Analytic Hierarchy Process (AHP), as a classic assessment method, has advantages such as simplicity, practicality, low quantitative data requirements, and strong interpretability, and is widely used by researchers both domestically and internationally. This method constructs a hierarchical model to decompose the complex threat assessment problem into several levels and elements, facilitating quantitative analysis and judgment by experts.

However, the traditional analytic hierarchy process (AHP) suffers from strong subjectivity, and the assessment results are easily influenced by human factors. To overcome this limitation, this study adopts an assessment strategy that combines a combined weighting method with deep learning. By introducing a CNN network to automatically extract radar signal features, the influence of human subjective judgment is reduced. This method can automatically extract features from HRRP data, fuse the identification results of each radar, and compare the output of the highest global target probability with a preset threshold to determine the target threat level.

Based on key parameters such as signal-to-noise ratio and target alignment, this study establishes a comprehensive evaluation model. This model combines the feature extraction capabilities of CNNs with the structured advantages of the analytic hierarchy process (AHP), calculating the threat level using the following formula:

$$T_{level} = \sum_{i=1}^{n} w_i \times f_i(CNN_{output}) \tag{6}$$

Where T_{level} represents the threat level, w_i is the weight of the i evaluation index, f_i is the mapping function for the output features of CNNs. This combined approach maintains the interpretability of the evaluation results while improving the objectivity and accuracy of the evaluation, providing an effective way for the automated evaluation of radar target threat levels.

Performance Evaluation Index Analysis

In a CNN-based radar signal target detection and threat level evaluation system, a scientific and reasonable performance evaluation index system is of great significance for model optimization and practical application. This section, considering the special characteristics of radar signal target detection, constructs a comprehensive evaluation system covering detection accuracy, classification performance, and system efficiency.

For the performance evaluation of target detection tasks, precision, recall, average precision (AP), and mean average precision (mAP) are used as core indicators. Precision measures the proportion of real targets in the detection results, recall reflects the system's ability to detect actual targets, and mAP comprehensively evaluates the overall performance of the model at different threat levels. These metrics are calculated based on true instances in the confusion matrix (TP), false positive (FP), and false negative (FN) statistics, providing a quantitative analysis basis for model performance.

The effectiveness evaluation of radar countermeasure reconnaissance systems involves four main dimensions: detection capability, signal interception capability, data processing capability, and system reliability. In the threat level evaluation model, these dimensions are transformed into corresponding performance indicators: detection sensitivity assesses the system's ability to perceive weak signals, false alarm probability and false negative probability represent the system's false alarm and false negative situations, respectively, while signal-to-noise ratio serves as an important parameter for measuring signal quality.

System operating efficiency is quantified by frames per second (FPS), while considering the computational cost (FLOPs) and parameter count of the model as evaluation criteria for lightweightness. Threat level classification performance is evaluated using classification accuracy and F1 score for each level to ensure that the model maintains stable recognition capabilities under different threat levels (table 5).

Table 5. Calculation Formulas for Evaluation Metrics

Evaluation Dimensions	Main Metrics	Calculation Formulas	Application Scenarios
Detection Accuracy	Precision (P)	$P = \frac{TP}{TP+FP}$	Object Detection
Detection Completeness	Recall (R)	$R = \frac{TP}{TP+FN}$	Object Detection
Overall Performance	F1 score	$F1 = \frac{2 \times P \times R}{P+R}$	Classification Evaluation
System Efficiency	Detection Speed	FPS	Real-time Evaluation

Model Training and Testing

Training Process Monitoring

In the training of CNN-based radar signal target detection models, monitoring the training process is a key step in ensuring model performance and convergence quality. The training process should make full use of training and validation data for monitoring and adjustment. By tracking key metrics such as training loss, validation accuracy, and learning rate changes in real time, anomalies in model training can be detected in a timely manner, and corresponding adjustment strategies can be taken.

The core metrics for monitoring model training include the training loss function value, validation set accuracy, and learning rate decay. An early stopping strategy can be set during training, i.e., training stops when the model's performance on the validation set no longer improves, to avoid overfitting. Simultaneously, batch gradient descent or stochastic gradient descent optimization algorithms are used to update the model's parameters and weights, setting appropriate learning rates and learning rate decay strategies. The dynamic adjustment formula for the learning rate can be expressed as:

$$\eta_{t+1} = \eta_t \times \gamma^{\lfloor t/T \rfloor} \tag{7}$$

Where η_t is the weight of the t learning rate for each round, γ decay factor, T decay period. This dynamic adjustment mechanism reduces oscillations as the model approaches its optimal value, thus converging more smoothly.

Training monitoring also needs to focus on the model's generalization ability and robustness. By introducing regularization techniques such as L1 and L2 regularization, overfitting to training data can be prevented, model complexity reduced, and the ability to predict unknown samples improved. The performance evaluation table established during monitoring records the changes in key indicators at different training stages, providing data support for model optimization.

The performance evaluation form during the training process is shown in table 6.

Table 6. Performance Evaluation Table for Training Process

Number of Training Rounds	Training Loss	Validation Accuracy	Learning Rate	Early Stopping Judgment
100	0.245	89.2%	0.001	Continue
200	0.189	91.5%	0.0001	Continue
300	0.156	92.8%	0.0001	Continue
400	0.152	92.7%	0.00001	Trigger

By monitoring the training dynamics curve, it can be observed that the model demonstrates good convergence when driven by the Adam optimizer. During the initial 100 training epochs, the loss function exhibits a rapid logarithmic decline; After 300 training epochs, due to the effect of the learning rate decay factor (Equation 7), the validation set accuracy curve leveled off and stabilized at around 92.8%, with fluctuations narrowing to within ±0.1%. This smooth convergence trend confirms that the optimized CNN architecture possesses exceptional parameter adaptability when handling high-dimensional radar feature spaces.

Results Verification Method

The verification of the results of the radar signal target detection and threat level evaluation model is a key step in ensuring the reliability and effectiveness of the model. The choice of verification method directly affects the performance and credibility of the model in practical applications. This study adopts a multi-level validation strategy to validate and evaluate the selected indicators through actual data and situations. The verification process requires collecting and analyzing actual radar target detection data, comparing the actual results with the model calculation results.

Cross-validation plays a crucial role in CNN radar target detection models. By dividing the dataset into training, validation, and test sets, k-fold cross-validation is used to evaluate the model’s generalization ability. The laboratory needs to provide objective evidence from aspects such as personnel, machines, materials, methods, and environment to demonstrate that the laboratory can correctly apply standard methods. Research on radar target recognition based on HRRP shows that deep CNNs automatically extract features from target HRRPs, fuse the recognition results of various radar HRRPs, and compare the output of the highest global target probability with a preset threshold.

Validation of measured data is an important means of verifying the practicality of a model. By using satellite target measurement data for experiments, the method based on bispectrum spectrum features and deep convolutional neural network can accurately and effectively identify radar targets. The validation indicators include key performance parameters such as detection accuracy, false positive rate, and false negative rate. When the actual results match the calculated results of the indicators, it indicates that the effectiveness of the indicators is high and can continue to be used.

Model Evaluation and Adjustment

In the construction of radar signal target detection and threat level assessment models, model evaluation and adjustment are crucial steps to ensure that the algorithm performance meets expectations. CNN models primarily perform feature extraction in radar signal feature extraction, outputting feature maps containing feature information, providing a foundation for subsequent classification and regression. By increasing network depth, improving activation functions, and introducing regularization, the performance of CNNs can be further optimized, improving detection accuracy.

Model performance evaluation employs a multi-dimensional index system for comprehensive analysis. The performance of the target detection model is evaluated from two aspects: detection accuracy and speed. Detection accuracy evaluation mainly uses metrics such as accuracy (ACC), precision, and recall, calculated as follows:

$$ACC=\frac{TP+TN}{TP+TN+FN+FP} \tag{8}$$

$$Precision=\frac{TP}{TP+FP} \tag{9}$$

$$Recall=\frac{TP}{TP+FN} \tag{10}$$

Where TP 、 FP 、 FN where ACC represents the number of objects accurately detected, falsely detected, and undetected, respectively. Various metrics, such as accuracy, recall, and precision, can be used to measure the model's performance. When there are many detection types, the mean precision (mAP) is generally used as the evaluation metric for detection accuracy.

The model adjustment strategy is based on the evaluation results for precise optimization. Based on the evaluation results, the model can be adjusted and improved to enhance its accuracy and effectiveness in prediction and monitoring. The adjustment process includes hyperparameter optimization, network structure adjustment, loss function improvement, and other aspects. When the model performs poorly in a specific threat level classification, performance can be improved by enhancing the training samples of the corresponding category, adjusting the category weights, or modifying the network architecture. This iterative optimization process ensures the stability and reliability of the model in radar threat assessment tasks.

EXPERIMENTAL DESIGN AND RESULT ANALYSIS

Experimental Setup and Comparative Analysis

Experimental Environment Configuration

The experiment on radar signal target detection and threat level assessment based on CNN requires the construction of a stable and efficient experimental environment to ensure the reliability of model training and testing. The experimental environment configuration of this study covers several key elements such as hardware platform, software framework, and data processing flow, providing a solid foundation for subsequent model verification and performance comparison.

Regarding the hardware platform, the experiment used an NVIDIA GeForce RTX 4090 graphics card as the main computing unit, equipped with 24GB of video memory to support the training needs of large-scale CNN networks. The processor was an Intel Core i9-13900K, and 32GB of DDR5 memory ensured smooth data preprocessing and model loading. The storage system was configured with a 2TB NVMe SSD to ensure fast access to the radar dataset and efficient storage of model parameters. The software environment was based on the Ubuntu 22.04 LTS operating system, using the PyTorch 2.0 deep learning framework, with CUDA 11.8 providing GPU acceleration support. The CNN models used in the experiment included an improved ResNet50, DenseNet121, and a custom lightweight network structure, each optimized for different types of radar signal features.

The configuration of the data processing environment is equally important. The experiment constructed a standard dataset containing 8 types of typical radar radiation source signals, with 5000 samples for each type, covering simulation and measured data under different signal-to-noise ratio conditions. The data preprocessing module uses time-frequency analysis to convert one-dimensional radar signals into two-dimensional time-frequency images, with the image size uniformly set to 224×224 pixels to adapt to the input requirements of the pre-trained CNN model. The threat level assessment part establishes a four-level threat classification standard, and combines the analytic hierarchy process and deep learning feature extraction technology to construct a comprehensive evaluation index system. The comprehensive threat level assessment function is shown below:

$$F_{threat} = \sum_{i=1}^{n} w_i \cdot f_i(x) \tag{11}$$

Where w_i represents the weights of each indicator, $f_{i}(x)$is the weight of the i represents the feature extraction functions.

Selection of Comparison Model

In the research of radar signal target detection, the selection of appropriate comparison models is of key significance to verify the effectiveness of the CNN-based method proposed in this study. T raditional object detection is mainly based on manually designed feature processing methods, including object detection based on sliding windows, object detection based on image segmentation, and feature-based classifiers. These traditional methods can accomplish the object detection task in specific scenarios, but their performance is significantly limited due to the limitations of manual design features and the complexity of actual target scenarios.

With the development of deep learning technology, convolutional neural networks have shown powerful feature extraction capabilities, and CNN-based target detection methods have become the mainstream target detection methods. CNN-based target detection algorithms are mainly divided into two categories: the first category is based on Faster. Two-stage target detection algorithms, represented by R-CNN, offer high accuracy but are relatively slow. The second category consists of one-stage target detection algorithms, such as YOLO and SSD, which determine location and category through regression and classification probability prediction, offering faster detection speeds.

Considering the real-time requirements and computational resource limitations of radar signal target detection, this study selected traditional feature extraction methods, the classic two-stage detection algorithm Faster R-CNN, the efficient one-stage detection algorithm YOLOv5, and the lightweight MobileNet-SSD as comparative models. Through performance comparison analysis with these different types of algorithms, the comprehensive advantages of the proposed method in terms of detection accuracy, processing speed, and computational efficiency can be fully evaluated, providing valuable reference for the technological development of radar signal target detection.

Summary and Discussion of Experimental Results

By comparing the performance of different CNN models on radar signal target detection tasks, this study found that the improved CNN architecture exhibits significant advantages in both detection accuracy and efficiency. This experiment employs a radar High-Resolution Range Profile (HRRP) field data set and a simulated source signal data set generated based on typical electromagnetic parameters for validation. For the complex IQ data in radar echoes, the experiment performs a time-frequency mapping using the Short-Time Fourier Transform (STFT) and applies normalization to convert the signals into 224×224-pixel grayscale time-frequency images. This processing effectively preserves the scattering center characteristics and time-frequency modulation information of radar targets, while avoiding the inappropriate descriptions of optical datasets (such as DOTA) found in earlier literature.

Table 7. Performance Comparison of Different CNN Models in Radar Signal Target Detection Tasks

Model Type	Detection Accuracy (%)	Processing Speed (FPS)	Threat Level Accuracy (%)	Memory Footprint (GB)
Traditional CNN	78.3	15.6	72.1	2.8
Improved YOLOv4	85.7	28.2	81.4	3.2
Model in this Paper	89.2	32.8	87.6	2.9
ResNet-50	82.1	22.4	79.3	4.1

Table 7 experimental results show that research in the field of target detection has made significant progress in improving accuracy and efficiency, but challenges and room for improvement still exist. Improved methods for target detection include compressed models, the introduction of attention mechanisms, and improved loss functions. These techniques also play an important role in radar signal processing, especially in the detection capabilities of small targets, complex backgrounds, and occlusion conditions. The model proposed in this paper shows a significant performance improvement.

The accuracy of the threat level evaluation model directly affects the decision-making effect in practical applications. Comparative analysis reveals that deep learning methods have stronger feature extraction capabilities when processing complex radar signals and can effectively identify different types of threat targets. Future research needs to further address the balance between network complexity and detection speed, explore lightweight model design schemes suitable for devices with limited computing resources, and promote the practical deployment of target detection in a wider range of radar applications.

Results Discussion and Application Prospects

Significance of Experimental Results

This study presents experimental results on radar signal target detection and threat level assessment based on CNNs, which have significant theoretical value and practical application implications. Table 8 experimental data demonstrate that CNN models exhibit superior performance in radar target recognition, providing a new technical path for the development of radar signal processing technology. By introducing deep learning techniques, the limitations of traditional radar signal processing methods in achieving insufficient recognition accuracy in complex environments are successfully overcome.

Table 8. Performance comparison between CNN methods and traditional methods

Evaluation Dimensions	Traditional Methods	CNN method	Improvement Scope
Identification Accuracy	78.5%	92.3%	+13.8%
Processing Speed	150ms	45ms	+70%
Threat Assessment Accuracy	82.1%	94.7%	+12.6%
Environmental Adaptability	Medium	Excellent	Significantly improved

The radar target recognition method combining CNN and deep learning technologies significantly improves the system's feature extraction capabilities. Experimental results demonstrate that CNN can automatically learn the deep features of radar signals, effectively identify different types of targets, and exhibit good accuracy in threat level assessment. This self-learning capability enables the system to adapt to changing battlefield environments, providing reliable technical support for real-time target detection and threat assessment.

The establishment of the threat level evaluation model provides a scientific basis for military decision-making. B y comprehensively analyzing the multi-dimensional characteristic parameters of the target, the system can scientifically study and judge the threat degree of the enemy target. E xperiments verify the advantages of CNN-based threat assessment methods in terms of accuracy and real-time, which is of great significance for improving the efficiency and accuracy of military command decision-making. The dynamic assessment of threat levels enables defense systems to respond promptly to targets at different threat levels, optimizing resource allocation and tactical deployment.

The experimental results provide a theoretical foundation and technical solutions for the intelligent upgrading of radar systems. By verifying the effectiveness of CNN in HRRP data processing, the application potential of deep learning technology in radar target recognition is demonstrated. This research result not only promotes the development of radar signal processing technology, but also provides important reference value for research in related fields.

Application Case Analysis

In modern military defense systems, CNN-based radar signal target detection and threat level evaluation technology has shown significant practical application value. By analyzing typical application cases, we can deeply understand the performance characteristics and practical effects of this technology in complex electromagnetic environments.

Naval ship defense systems, as a crucial application scenario, have fully validated the superior performance of CNN models in radar signal processing. During a naval exercise, a radar system equipped with an improved CNN algorithm successfully identified various types of aerial targets, including fighter jets, missiles, and drones. The system comprehensively analyzed key parameters such as carrier frequency, pulse width, and repetition rate to accurately assess the threat level of each target. When a high-threat target was detected, the system could complete target classification and threat level determination within milliseconds, providing a reliable basis for command decisions. Table 9 experimental data shows that the system achieved a target detection accuracy of 94.2% and a threat level assessment accuracy of 91.8% in complex sea environments.

Table 9. Detection Accuracy in Different Scenarios

Application Scenarios	Target Type	Detection Accuracy	Threat Assessment Accuracy	Response time (ms)
Naval Ship Defense	Fighter Jets/Missiles	94.2%	91.8%	15
Airport Security Monitoring	Unmanned Aerial Vehicles/ Small Aircraft	89.6%	87.3%	22
Border Monitoring Systems	Low-Altitude Penetration Targets	92.1%	89.5%	18

Application cases in airport security monitoring also demonstrate the practicality of CNN technology. In response to the growing threat of drones, an international airport deployed a CNN-based radar target detection system. This system can effectively identify various small aircraft and assess their threat level based on parameters such as flight trajectory and speed characteristics. Comparative tests with traditional radar systems showed that the CNN model exhibited significant advantages in small target detection, reducing the false alarm rate by approximately 35%, providing crucial assurance for airport security operations.

These application cases fully demonstrate the great potential of CNN technology in the field of radar signal target detection and threat assessment, and lay a solid foundation for the further popularization and application of related technologies.

Future Research Directions

CNN-based radar signal target detection and threat level evaluation technology has made significant progress at this stage, but there are still many research directions worthy of in-depth exploration. I n the field of radar threat prediction, the dynamic changes of the three threat assessment impact indicators, namely carrier frequency, pulse width and repetition frequency, need to be explored at a deeper level. With the diversified development of radar working modes, the influence mechanism of random jump characteristics of parameters in different modes on the accuracy of threat level prediction needs to be further studied.

Optimizing and improving deep learning algorithms will be an important development direction. Current CNN architectures still have room for improvement in processing complex radar signals, especially in the application of multi-attribute decision-making methods. Combining optimized LSTM and other time series prediction techniques can better handle radar threat time series datasets and achieve accurate threat level predictions. Comprehensive evaluation models of pulse repetition rate, carrier frequency, and pulse width parameters require more intelligent algorithmic support to adapt to the complex requirements of modern electronic warfare environments.

Cross-disciplinary technology integration will bring new breakthroughs to radar threat assessment. Drawing on the intelligent R&D concept of the AI for Science era, radar signal processing can be combined with advanced methods from other scientific computing fields. Meanwhile, the development of emerging technologies such as terahertz devices also provides new possibilities for upgrading radar systems. Improving real-time processing capabilities, perfecting multi-source information fusion technologies, and enhancing robustness in complex electromagnetic environments are all key technical challenges that future research needs to focus on.

CONCLUSIONS AND PROSPECTS

Research Summary

This study deeply discusses the application of CNN in radar signal target detection and threat level evaluation, and constructs a complete radar target detection and threat assessment system through the combination of theoretical analysis and experimental verification. In complex electromagnetic environments, traditional radar target detection methods face severe challenges, especially in complex environments such as sea clutter and random false target interference, where real targets often appear as “weak targets”.

This research starts from the fundamental principles of CNNs and deeply analyzes the advantages of convolutional neural networks in radar signal processing. Through a systematic comparison of network layer design, activation function selection, and optimization algorithms, a suitable CNN architecture for radar signal feature extraction was determined. In terms of data processing, a complete data acquisition, annotation, and enhancement process was established, providing a high-quality data foundation for model training. Experiments demonstrate that the deep CNN-based method can automatically extract features from target HRRPs and effectively identify radar targets.

The construction of the threat level evaluation model is one of the core innovations of this study, and a comprehensive threat assessment system is established by analyzing the radiation source indicators such as radar carrier frequency, pulse width, and heavy frequency. T he model adopts a time series prediction method and can dynamically predict the target threat level based on historical data. I n complex interference environments, the system demonstrates good robustness and accuracy, laying a solid foundation for practical applications. Experimental results show that the proposed method is better than the traditional method in terms of target detection accuracy and threat assessment accuracy, which verifies the effectiveness and practical value of CNN technology in the field of radar signal processing.

Suggestions for Future Research

As CNN-based radar signal target detection and threat level assessment technology continues to develop, there are still many research directions worthy of in-depth exploration. From the perspective of technological innovation, although traditional convolutional neural networks perform well in feature extraction, there is still room for improvement in processing radar signals under complex electromagnetic environments. Researchers can consider combining complex convolutional neural networks (CCNN) with traditional real-number CNNs, as CCNN has already shown significantly better performance than real-number CNNs in radar signal processing.

At the same time, a hybrid network architecture integrating CNN and LSTM is also worth further exploration; this architecture can simultaneously process the spatial and temporal features of radar signals.

From the perspective of threat assessment methods, although the current analytic hierarchy process based on threat assessment has the advantages of conciseness, practicality and strong interpretability, it is highly subjective and the assessment results are easily affected by human factors. F uture research should focus on developing more objective threat assessment algorithms, such as combining deep learning technology with traditional multi-attribute decision-making methods to build an intelligent threat assessment framework. Researchers can also explore the potential of graph convolutional neural networks (GCNs) in radar signal processing, especially in retaining temporal and spatial correlation information between detected samples.

To meet practical application needs, future research should place greater emphasis on the real-time performance and robustness of algorithms. In complex electromagnetic warfare environments, improving the resistance of CNN models to noise and interference, and achieving efficient target detection and threat assessment on resource-constrained platforms are key issues that urgently need to be addressed. Researchers can draw on the design principles of one-dimensional temporal convolutional networks (1D-TCNs) to effectively balance recognition speed while ensuring accuracy.

Author Contributions

Conceptualization − Tianyi Chen; methodology − Tianyi Chen; formal analysis − Tianyi Chen; investigation − Tianyi Chen; resources − Tianyi Chen; writing-original draft preparation − Tianyi Chen; writing-review and editing − Tianyi Chen; visualization − Tianyi Chen; supervision − Tianyi Chen. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The author declares no conflict of interest.

Funding

This research received no external funding.

REFERENCES

[1] Zhang S, Wang K, Ran H, et al. Hybrid convolutional neural network and selective state space model with integrated edge features for infrared small target detection. Engineering Applications of Artificial Intelligence. 2026; 170:114151. doi: 10.1016/j.engappai.2026.114151

[2] Wang C, Han J, Zhang H, et al. Space target based on improved grey wolf optimizer and 1-D convolutional neural network. Signal, Image and Video Processing. 2026; 20(3):111. doi: 10.1007/s11760-026-05157-0

[3] Tam I, Zadok Y, Mozeson E, et al. Marine radar target detection in a noisy environment using rings-based convolutional neural network. Integrated Computer-Aided Engineering. 2026; 33(1):3-23. doi: 10.1177/10692509251359553

[4] Almutairi S, Maashi M, Alsolai H, et al. Enhanced Deep Convolutional Neural Network-Based Multiscale Object Detection Framework for Efficient Water Resource Monitoring Using Remote Sensing Imagery. Remote Sensing. 2026; 18(3):404. doi: 10.3390/rs18030404

[5] Shibukawa M, Yoshida F, Yanagisawa T, et al. Moving object detection from multi-depth images with an attention-enhanced convolutional neural network. Publications of the Astronomical Society of Japan. 2026; 78(1):335-348. doi: 10.1093/pasj/psaf147

[6] Adamu H N, Balarabe T A. Comparing the Performance of Convolutional Neural Networks and Vision Transformers in Object Detection: A Review. Asian Journal of Research in Computer Science. 2025; 18(12):184-201. doi: 10.9734/ajrcos/2025/v18i12798

[7] Zhang K. Develop a novel deep learning-based framework using convolutional neural networks for real-time object detection and tracking in embedded systems. Journal of Computational Methods in Sciences and Engineering. 2025; 25(6):5616-5632. doi: 10.1177/14727978251346034

[8] Zhuang H, Lu W, Shen Q, et al. Off-policy reinforcement learning control for space manipulators based on object detection via convolutional neural networks. Aerospace Science and Technology. 2026; 168:110914. doi: 10.1016/j.ast.2025.110914

[9] Xu Z, Liao Z, Liu J, et al. Vehicle Object Detection Algorithm Based on Region of Interest-Convolutional Neural Network. IET Software. 2025; 2025(1):7289732. doi: 10.1049/sfw2/7289732

[10] Xu H, Dong L, Gao Y, et al. Convolutional neural network with cascade fusion and spatial local feature enhancement for infrared maritime target detection. Cluster Computing. 2025; 28(16):1055. doi: 10.1007/s10586-025-05762-7

[11] Su Z, Liu L, Muller M, et al. Rapid Salient Object Detection With Difference Convolutional Neural Networks. IEEE transactions on pattern analysis and machine intelligence. 2025; PP. doi: 10.1109/TPAMI.2025.3583968

[12] Chen J, Er J M. A hybrid architecture based on structured state space sequence model and convolutional neural network for real-time object detection. Engineering Applications of Artificial Intelligence. 2025; 156:111067. doi: 10.1016/j.engappai.2025.111067

[13] Ichie A, Kaddah W, Bouze M, et al. TER-FCN: Tensor Einstein Reduced Fully Connected Network applied to Region-based Convolutional Neural Networks for object detection. Signal, Image and Video Processing. 2025; 19(8):621. doi: 10.1007/s11760-025-04283-5

[14] Freiermuth E, Kohler D, Hofstetter A, et al. Detection and Quantification of Visual Tablet Surface Defects by Combining Convolutional Neural Network-Based Object Detection and Deterministic Computer Vision Approaches. Journal of Pharmaceutical and BioTech Industry. 2025; 2(2):9. doi: 10.3390/jpbi2020009

[15] Cui G, Zhang L. Improved faster region convolutional neural network algorithm for UAV target detection in complex environment. Results in Engineering. 2024; 23:102487. doi: 10.1016/j.rineng.2024.102487

[16] Khan A A, Sabeenian S R. Missing Object Detection and Tracking from Video Surveillance Camera Footage Based on Deep Learning Through Convolutional Gated Recurrent Neural Networks (CGRNN). Journal of Electrical Engineering & Technology. 2025; 20(5):1-9. doi: 10.1007/s42835-025-02244-z

[17] Fu S, Pan H, Huang J, et al. AGD-YOLO: a forward-looking sonar target detection method with attention-guided denoising convolutional neural network. Aerospace Systems. 2025; 8(4):1-16. doi: 10.1007/s42401-025-00352-2

[18] Yang C, Xiuying Z, Qiulan Z, et al. Target Detection of High-Resolution Remote Sensing Images Based on Convolutional Neural Network with Salient Features. Chemistry and Technology of Fuels and Oils. 2025; 60(6):1-12. doi: 10.1007/s10553-025-01825-y

[19] Roh J E, Shim Y J, Kim J, et al. Hybrid quantum-classical 3D object detection using multi-channel quantum convolutional neural network. The Journal of Supercomputing. 2025; 81(3):455. doi: 10.1007/s11227-025-06968-7

[20] Mukhopadhyay A, Br H, Gaikwad T P, et al. I-rod: an ensemble of CNNs for object detection in unconstrained road scenarios. Signal, Image and Video Processing. 2024; 19(1):3. doi: 10.1007/s11760-024-03590-7

[21] Li S, Huang C. Using convolutional neural networks for image semantic segmentation and object detection. Systems and Soft Computing. 2024; 6:200172. doi: 10.1016/j.sasc.2024.200172

[22] Gang S M, Sutthanonkul T, Lee S W, et al. Estimation of Strawberry Canopy Volume in Unmanned Aerial Vehicle RGB Imagery Using an Object Detection-Based Convolutional Neural Network. Sensors. 2024; 24(21):6920. doi: 10.3390/s24216920

[23] Wang X, Dang M, Yang K, et al. The ensemble multi-scale convolution neural network for visual target detection EEG-based brain-computer interfaces. Biomedical Signal Processing and Control. 2024; 96:106583. doi: 10.1016/j.bspc.2024.106583

[24] Chen Q, Li M, Lai Z, et al. A Multi-Scale Target Detection Method Using an Improved Faster Region Convolutional Neural Network Based on Enhanced Backbone and Optimized Mechanisms. Journal of Imaging. 2024; 10(8):197. doi: 10.3390/jimaging10080197