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Application of SAR Target Recognition Based on Electromagnetic Scattering Feature Fusion in soybean Detection

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ABSTRACT

In the context of the rapid development of agricultural intelligence, the use of target recognition technology to detect grain phenomena can effectively ensure food safety. Synthetic aperture radar (SAR) technology has been widely used in the field of target recognition due to its high resolution and good anti - jamming ability. In this study, a SAR target recognition method based on electromagnetic scattering features is proposed. This method fuses the deep-learning algorithm YOLOv5 with electromagnetic scattering features to achieve target recognition and classification, and applies it to soybean classification and detection, aiming to provide an efficient and reliable solution for grain detection. Through theoretical analysis and experimental verification, this study demonstrates that the proposed method achieves a high maximum accuracy of 95.7% in identifying complex targets such as soybeans, indicating its excellent performance.

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KEYWORDS: Electromagnetic Scattering Feature, SAR Target Recognition, Yolov5, Soybean Detection.

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INTRODUCTION

Food security is a strategic issue that bears on the national economy and people's livelihood, and grain quality grade detection is a key link in safeguarding the order of grain circulation and improving the efficiency of agricultural production. As an active microwave remote sensing technology, synthetic aperture radar (SAR) has the observation capability that is not restricted by illumination and meteorological conditions. It can penetrate vegetation and shallow media to obtain target electromagnetic scattering information, thus providing a non-contact solution for grain detection.

Electromagnetic scattering characteristics are the core basis of SAR imaging, which can reflect the physical properties of targets, such as shape, dielectric constant, surface roughness, etc. (He et al., 2024; Zhang et al., 2023; Ding et al., 2018; Ding et al., 2017). These characteristics are insensitive to changes in azimuth angle and differences in resolution, and also robust to the Signal-to-Noise Ratio (SNR). Therefore, methods based on electromagnetic scattering characteristics can effectively identify SAR targets (Wu et al., 2024).Grain targets of different quality grades produce significant differences in scattering responses due to variations in kernel plumpness, moisture content, surface conditions, and other aspects. However, the characterization capability of a single electromagnetic scattering feature is limited, making it difficult to fully depict the complex properties of grain targets. Meanwhile, the inherent speckle noise in SAR images further affects the accuracy of feature extraction.

Feature extraction technology is mainly used to obtain the geometric features, transform domain features, electromagnetic scattering features and neural network features of targets. Scholars have acquired target scattering information through methods such as polarization decomposition and scattering center extraction, which provides a physical basis for recognition tasks (Xing et al., 2025). Traditional electromagnetic scattering features (e.g., backscattering coefficient, polarization ratio, texture features, etc.) can effectively reflect the physical properties of targets. However, the adaptability of a single feature to complex scenarios is insufficient, and it is necessary to improve the characterization capability through feature fusion.Many researchers have applied machine learning methods to target detection (Zhang et al., 2019; Zhao et al., 2023; Zhang et al., 2021; Zhang et al., 2020) and automatic target recognition (Sun et al., 2019; Samadi et al., 2019; Sunkara et al., 2022; Huang et al., 2020; Shin et al., 2024; He et al., 2021; Kechagias et al., 2021). Based on CNN, a method for SAR image recognition was proposed, which realized supervised terrain classification and verified the advancement of the fusion of physical features and deep learning (Zhang et al., 2017).

In the agricultural field, ground-penetrating radar (GPR) and electromagnetic induction (EMI) technologies have been applied to assess soil properties, conditions, processes and their spatiotemporal variations (Pathirana et al., 2023). SAR has been widely used in crop classification, crop growth status detection and soil moisture detection. In addition, SAR remote sensing has great development potential in the future with the help of accurate and efficient modeling of optical and electromagnetic scattering, as well as deep integration with machine learning (Yun et al., 2019).

Researchers utilized phenology-like data from SAR satellite images and identified rice distribution by integrating deep learning (DL) technology (Onojeghuo A O et al., 2023). In recent years, deep learning technology has demonstrated remarkable advantages in SAR target recognition. Among these techniques, the YOLOv5 algorithm has been widely applied to various target detection tasks due to its fast detection speed, high accuracy, and strong generalization capability (Kumar et al., 2023; Gao et al., 2024; Zhou et al., 2025; Lan et al., 2024; Zhao et al., 2025).

For complex field environments, Li et al. proposed a lightweight network based on YOLOv5 for the classification and detection of diseases and insect pests on rice leaves, which verified the effectiveness of the improved YOLOv5 algorithm in complex SAR scenarios (Li et al., 2024).However, existing studies mostly focus on large-scale targets such as ships and vehicles, with few applications targeting small-sized, weak-scattering objects like grains (Peng et al., 2024; Zhu et al., 2023).Chen et al. developed a lightweight model named RALSD-YOLO for the recognition of phenotypic information of corn tassels, which improved the accuracy and efficiency of small object detection (Chen et al., 2025).

To address the problem of low accuracy in grain quality classification and detection when relying solely on SAR target recognition methods based on electromagnetic scattering features—a challenge caused by the small size of grain particles and complex background environments—this study integrates electromagnetic scattering features with the YOLOv5 algorithm to achieve complementary advantages between physics-driven and data-driven approaches.

A SAR target recognition method based on the fusion of YOLOv5 and electromagnetic scattering features is proposed herein. Specifically, the target physical attribute information provided by electromagnetic scattering features is embedded into the neck network of YOLOv5 to construct a fusion model, which is then applied to the classification and detection of soybean seeds.

METHODS

1 Extraction of electromagnetic scattering characteristics

Considering the characteristics of soybean targets, this study selects the following key features:

a. One-dimensional scattering features: Backscattering coefficient (σ^0), which reflects the overall scattering intensity of soybean targets and is obtained via radiometric calibration of SAR images. Significant differences in the backscattering coefficient exist among different types of soybeans due to variations in grain density and moisture content.

b. Two-dimensional texture features: Contrast, correlation, energy and entropy extracted based on the Gray-Level Co-occurrence Matrix (GLCM), which reflect the arrangement mode and surface roughness of soybean grains. Feature calculation is implemented using the imgproc module of OpenCV.

c. Polarimetric scattering features: Scattering entropy (H) and anisotropy (A) extracted from polarimetric SAR data, which reflect the diversity and concentration degree of target scattering mechanisms and are obtained through polarimetric decomposition algorithms.

The feature extraction process is as follows: First, select the Region of Interest (ROI) from the preprocessed SAR images and calculate the backscattering coefficient for the ROI area; Second, convert the images into grayscale images, compute the Gray-Level Co-occurrence Matrix (GLCM) using OpenCV and extract the texture features; Finally, perform Cloude-Pottier decomposition on the polarimetric SAR data to obtain the polarimetric scattering feature parameters.

2 YOLOv5 algorithm

The YOLOv5 algorithm adopts a modular design and is mainly composed of four parts: the input end, backbone network, neck network, and detection head.

The input end enhances the generalization capability of the model through operations such as Mosaic data augmentation and adaptive anchor box calculation. The backbone network adopts a CSPDarknet structure, which effectively extracts multi-scale deep features of images via residual connections and cross-stage partial feature fusion. The neck network employs a structure combining FPN (Feature Pyramid Network) and PAN (Path Aggregation Network) to achieve feature fusion during upsampling and downsampling processes, thereby enhancing the detection capability for multi-scale targets. The detection head outputs the category probability and position coordinates of targets simultaneously through its classification branch and regression branch, completing target detection and classification.

The calculation formulas for the target center points b_x, b_y and the target width and height b_w, b_h finally predicted by the YOLOv5 algorithm are as follows：

$$b_x=(2*\sigma(t_x)-0.5)+c_x \tag{1}$$

$$b_y=\left(2*\sigma\left(t_y\right)-0.5\right)+c_y \tag{2}$$

$$b_w=p_w*\left(2*\sigma(t_w)\right)^2 \tag{3}$$

$$b_{\mathrm{h}}=p_{\mathrm{h}}*\left(2*\sigma(t_{\mathrm{h}})\right)^2 \tag{4}$$

In Formulas (1) and (2), t_x,t_y represent the offsets of the predicted target center point from the top-left corner of the corresponding grid, c_x is the x-coordinate of the top-left corner of the corresponding grid, and c_y is the y-coordinate of the top-left corner of the corresponding grid. In Formulas (3) and (4), sigmoid denotes the sigmoid function, which can constrain the predicted offsets to prevent the predicted center point from exceeding the corresponding grid region.

YOLOv5 adopts a matching strategy based on width and height ratios. For each manually labeled ground truth box, the width ratios (*w1/w2, w2/w1*) and height ratios (*h1/h2, h2/h1*) between the box and different anchor prior boxes are calculated respectively.

$$r_w=\frac{w_{gt}}{w_{at}} \tag{5}$$

$$r_{\mathrm{h}}=\frac{\mathrm{h}_{gt}}{\mathrm{h}_{at}} \tag{6}$$

$$r_w^{max}=\max\left(r_w,\frac{1}{r_w}\right) \tag{7}$$

$$r_{\mathrm{h}}^{max}=\max\left(r_{\mathrm{h}},\frac{1}{r_{\mathrm{h}}}\right) \tag{8}$$

$$r^{max}=\max(r_w^{max},r_{\mathrm{h}}^{max}) \tag{9}$$

$$r^{max}<anchor_t \tag{10}$$

Find the maximum value among the width ratios (*w1/w2, w2/w1*) and height ratios (*h1/h2, h2/h1*) between the manually labeled ground truth box and the anchor prior box, and take this value as the matching ratio between the manually labeled ground truth box and the anchor prior box.The core advantage of the YOLOv5 algorithm lies in its efficient feature extraction and fusion capability, which enables it to automatically learn the discriminative features of targets through end-to-end training.

3 Feature Fusion

The feature layer fusion strategy is adopted for the integration of the YOLOv5 algorithm and electromagnetic scattering features. The core idea is to organically combine physical scattering features with deep features to construct a more discriminative comprehensive feature vector. Electromagnetic scattering features provide physical attribute information of targets with clear physical meanings, which can effectively distinguish the essential differences among soybeans of different quality grades; in contrast, the deep features extracted by YOLOv5 possess strong nonlinear expression capabilities, enabling them to capture complex patterns and noise-robust features in images, thus forming a complementary relationship between the two types of features.

The normalized electromagnetic scattering feature vector is embedded into the neck network of YOLOv5. A combination of concatenation fusion and attention weighting is employed: first, the electromagnetic scattering features are concatenated with the deep features output by the FPN-PAN network; then, the fused features are weighted to highlight the key feature information for soybean classification and suppress noise interference.

4 Fusion identification method flow

Based on the aforementioned mechanism, a complete SAR target recognition workflow is designed, with the specific steps shown (Figure 1).

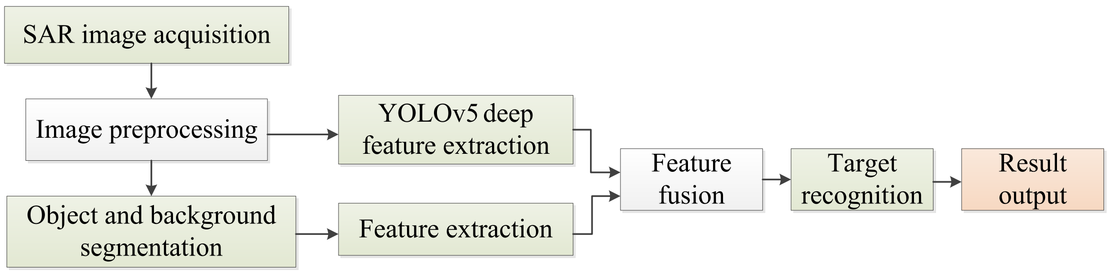

Figure 1 Target Recognition Workflow Based on Feature Fusion

EXPERIMENT

1 Preparation of Experimental Data

a. Soybean sample collection

The soybean grain image database is sourced from an open-source deep learning dataset website (https://data.mendeley.com/datasets/v6vzvfszj6/6). Under the database folder, there are 4 major categories of datasets, namely the damaged soybean dataset, broken soybean dataset, spotted soybean dataset, and intact soybean dataset.

b. SAR image acquisition

An X-band SAR system was used for imaging soybean samples, with the imaging parameters set as follows: operating frequency of 9.6 *GHz*, polarization mode of VV polarization, resolution of 0.3*m*×0.3*m*, imaging distance of 100*m*, and viewing angle of 30°. To ensure data consistency, all samples were maintained with uniform placement, lighting conditions, and ambient temperature during imaging. A total of 25 SAR images were acquired to construct an experimental dataset for soybean category classification.

c. Dataset partitioning and labeling

The LabelImg tool was used to annotate soybean samples in SAR images, The four data sets of "Skin-damaged soybeans", "Broken soybeans", "Spotted soybeans" and "Intact soybeans" were selected from the database. The dataset was divided into a training set and a test set at a ratio of 7:3, where the training set was used for model training and parameter optimization, and the test set was used for model performance evaluation (Table 1).

Table 1. Image database data

Database	Training Set	Test Set
Skin-damaged soybeans	789	338
Broken soybeans	701	301
Spotted soybeans	741	317
Intact soybeans	841	360

2 Experimental Procedures

a. SAR Image Preprocessing

Preprocessing serves as the preliminary preparation for image classification and recognition, which can eliminate discrepancies between the original image and the processed image caused by factors such as distortion, underexposure, and overexposure during image acquisition, transmission, and transformation. The following preprocessing operations are implemented based on OpenCV.

The Lee filtering algorithm is adopted with a filtering window size of 5×5, implemented via the filter2D function of OpenCV to remove speckle noise in SAR images. Using the imaging parameters and control point information of the SAR system, image translation and rotation correction are achieved through the warpAffine function of OpenCV to eliminate imaging distortion. The histogram equalization algorithm is employed, and the equalizeHist function of OpenCV is used to adjust the grayscale distribution of images, thereby enhancing image contrast.

When processing images with OpenCV, the image is first converted to the BGR format, then transformed into the RGB format suitable for computer vision tasks, and further converted to the HSV format (Figure 2-4). Images in the HSV format can effectively distinguish color information from brightness information and place them in separate channels, thereby reducing the impact of light on color recognition and laying the groundwork for subsequent image grayscale processing. A grayscale image acts as an intermediate version between binary images and color images; in the GRAY color space, each pixel can be represented by a single numerical value (Figure 5).

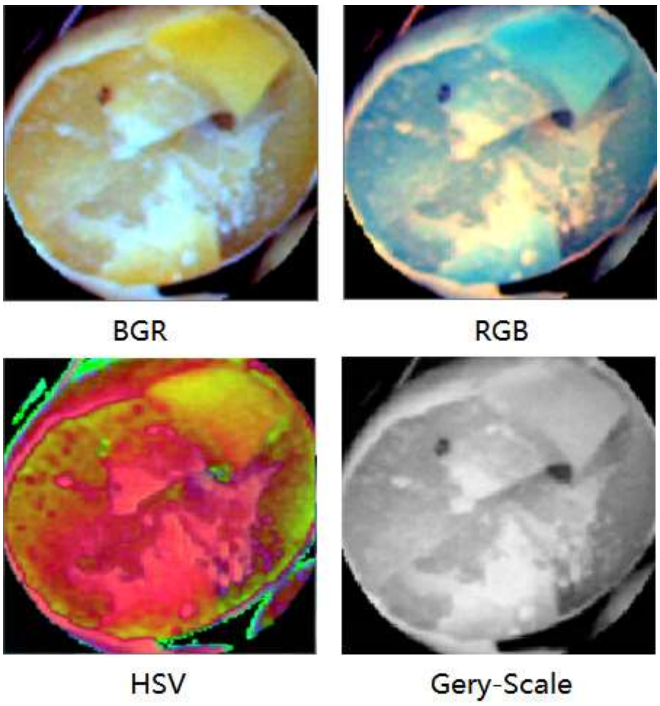

Figure 2 Conversion results of soybean image format

Binarization processing of soybean grain images can effectively separate targets from the background and reduce redundant information in the images, laying a solid foundation for subsequent image recognition. Image binarization can improve the efficiency of image processing, simplify image features, and facilitate image processing and storage (Figure 3).

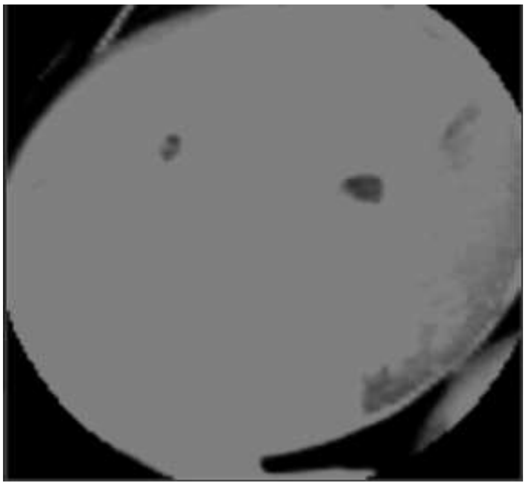

Figure 3. Binarized grayscale image

b. Electromagnetic scattering feature extraction

Radiometric calibration is performed on the preprocessed SAR images to convert the grayscale values into backscattering coefficients (σ^0). The calculation formula is as follows:$\sigma^0 = 10\log_{10}(DN^2 / G_0)$,where DN denotes the grayscale value of the image and G_0 denotes the radar system gain.

The SAR images are converted into grayscale images using the cvtColor function of OpenCV. Then, the Gray-Level Co-occurrence Matrix (GLCM) for a 5×5 window is calculated to extract four feature parameters: contrast, correlation, energy, and entropy. Cloude-Pottier decomposition is performed on the fully polarimetric SAR data to obtain the scattering entropy (H) and anisotropy (A) features. The feature values are mapped to the range [0,1] through min-max normalization.

c. Improvements and Training of YOLOv5 Model

The feature fusion module is added to the neck network (FPN-PAN) of YOLOv5 to concatenate the 4-dimensional electromagnetic scattering features with the deep features; the anchor box parameters are adjusted, and the size of adapted anchor boxes is recalculated based on the statistical results of soybean sample sizes.The number of training epochs is set to 100, the initial learning rate is 0.001, a cosine annealing learning rate scheduling strategy is adopted, and the weight decay is set to 0.0005.

The soybean classification results of the training set are obtained through training (Figure 4). The SAR images of the test set are input into the trained fusion model to output the soybean classification results (Figure 5).

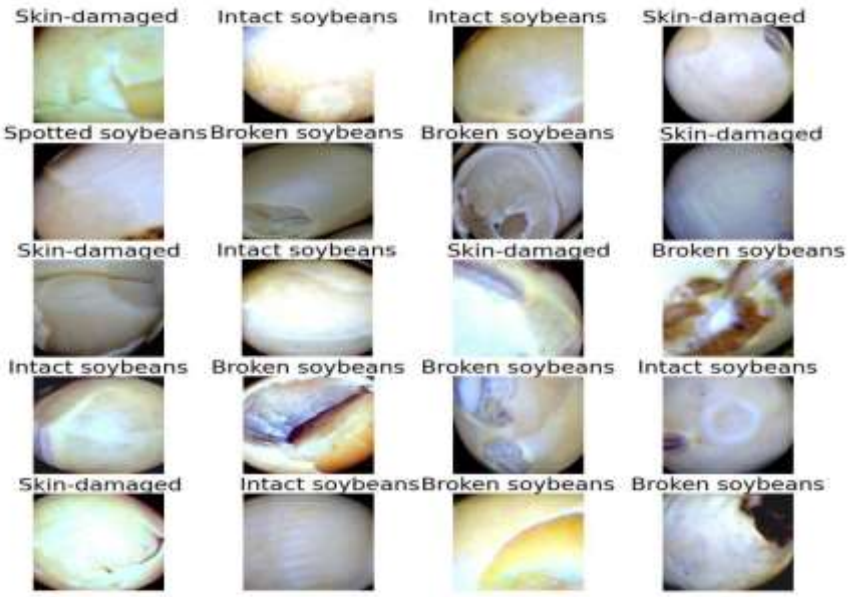

Figure 4 Soybean training classification results

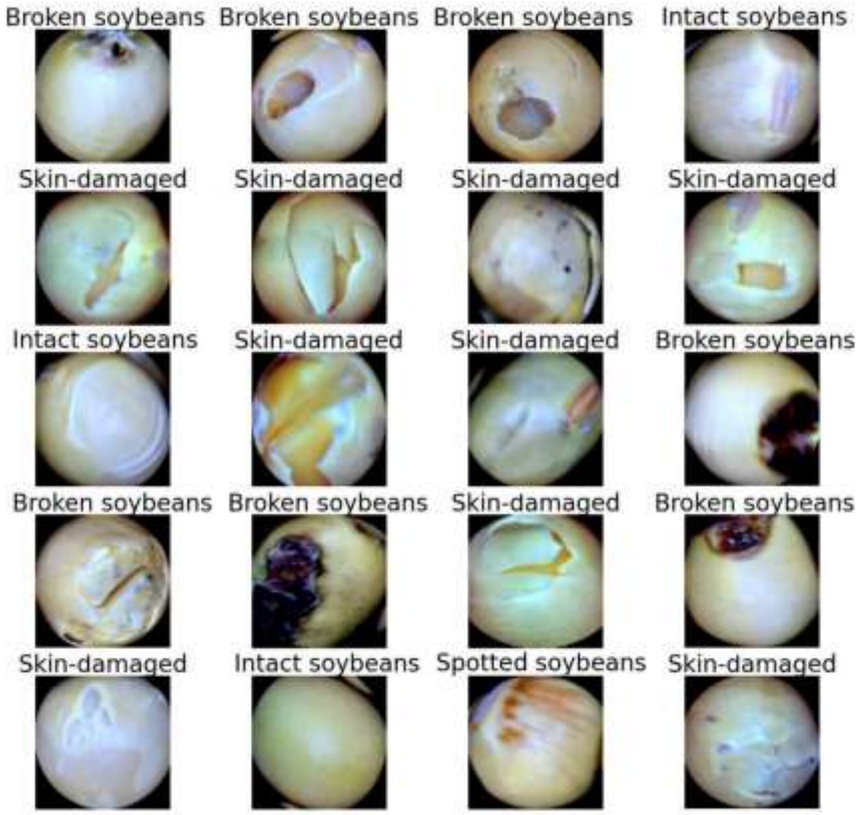

Figure 5 Soybean Test Classification Results

RESULT AND DISCUSSION

After the model training is completed, soybean images are imported for feature recognition. There are four types of soybean features in the dataset, namely damaged soybeans, broken soybeans, spotted soybeans, and intact soybeans. Therefore, four types of soybean features can be detected during defect detection. The recognition results of various soybean features (Figure 6), where (a) represents intact soybeans, (b) represents spotted soybeans, (c) represents damaged soybeans, and (d) represents broken soybeans.

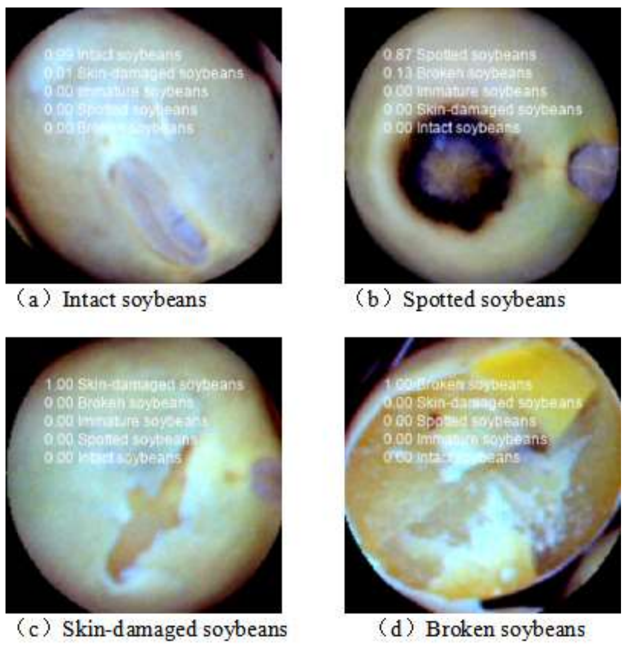

Figure 6 Soybean Feature Recognition Results

Precision and *loss* are adopted as the model performance evaluation metrics. *Precision* reflects the accuracy of the model's classification results, while *loss* reflects the severity of the model's prediction errors. The calculation formula for precision is as follows:

$$Precision = TP / (TP + FP) \tag{11}$$

Where, *TP* (True Positive) denotes the number of target samples correctly classified, *TN* (True Negative) denotes the number of non-target samples correctly classified, and *FP* (False Positive) denotes the number of samples incorrectly classified as target samples.

The *loss* of YOLOv5 mainly consists of three components: *Location loss* L_{DIoU}, *Classes loss* L_{loc} and *Objectness loss* L_{obj}.

$$Loss=\lambda_1 L_{DIoU}+\lambda_2 L_{loc}+\lambda_3 L_{obj} \tag{12}$$

Where $\lambda_1,\lambda_2,\lambda_3$ are the balance coefficients.

The *localization loss* mainly calculates the Intersection over Union (*IoU*), which is used to measure the overlap degree between the predicted bounding box and the ground truth bounding box in object detection. Assuming the predicted bounding box is *A* and the ground truth bounding box is *B*, the expression for *IoU* is:

$$IoU=\frac{A\cap B}{A\cup B} \tag{13}$$

The *loss* function of *DIoU* is:

$$L_{DIoU}=1-IoU+\frac{\rho^2\left(b,b^{gt}\right)}{c^2} \tag{14}$$

where b and b^{gt} represent the center points of the predicted bounding box and the ground truth bounding box, respectively; ρ denotes the Euclidean distance between the two center points; and c denotes the diagonal distance of the smallest enclosing region of the predicted bounding box and the ground truth bounding box.

For *Classes loss*, YOLOv5 uses the binary cross-entropy function by default for calculation. The definition of the binary cross-entropy function is:

$$L=-y\log p-(1-y)\log(1-p)=\begin{cases} -\log p & ,y=1 \\ -\log(1-p) & ,y=0 \end{cases} \tag{15}$$

where y is the label corresponding to the input sample (1 for positive samples and 0 for negative samples), and p is the probability that the model predicts the input sample as a positive sample.

As the number of iterations increases, the *loss* decreases smoothly and approaches 0 at the 100th iteration. Meanwhile, the training precision continuously improves, exceeding 95% after 100 iterations, with the highest precision reaching 95.7%. This indicates that the feature recognition achieves relatively high accuracy (Figures 7, 8).

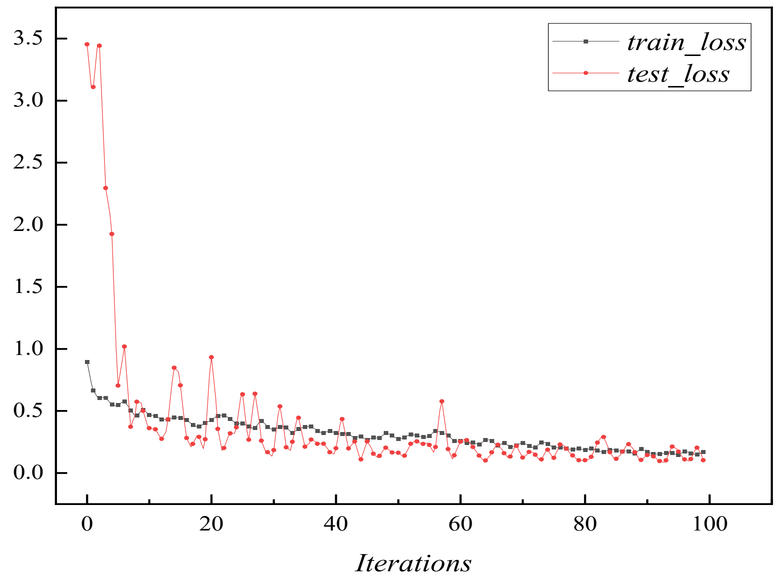

Figure 7. Training and testing losses

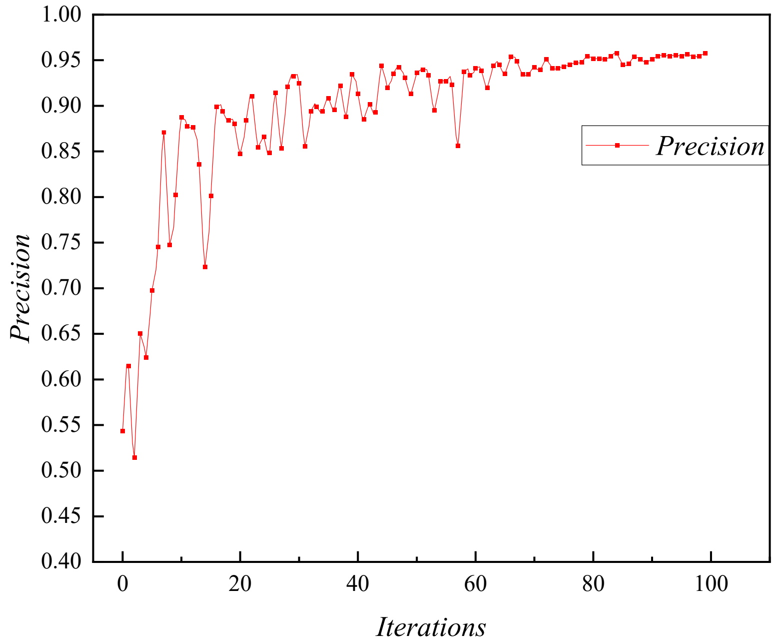

Figure 8 Precision variation

CONCLUSION

Aiming at the problem that traditional SAR grain detection methods have limited accuracy for small objects such as grain seeds, this paper proposes a SAR target recognition method based on the fusion of the YOLOv5 algorithm and electromagnetic scattering features. Taking the classification of soybean quality grades as the research object, theoretical analysis, model construction, and experimental verification have been completed, with the main conclusions as follows:

The fusion mechanism of the YOLOv5 algorithm and electromagnetic scattering features is clarified. Through the feature-level fusion strategy, the complementary advantages of physical mechanism-driven and data-driven approaches are realized, and the constructed comprehensive feature vector can more comprehensively characterize the characteristics of soybean targets; SAR image preprocessing and electromagnetic scattering feature extraction are implemented based on OpenCV, and the neck network of the YOLOv5 model is improved.

Experimental results show that the soybean classification accuracy of the fusion model reaches 95.7%, indicating high precision. This fusion method effectively solves the problem of accurate recognition of small objects such as grain seeds, and provides an efficient and objective technical solution for the intelligent detection of grain quality.

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