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Soybean Lodging Grade Classification Based on UAV Remote Sensing and Improved AlexNet Model

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Abstract

Soybean lodging severely impairs yield and quality, and its precise grading is a key prerequisite for intelligent agricultural management and loss assessment in agricultural insurance. Most existing studies have focused primarily on soybean lodging identification and lodging resistance evaluation, whereas methods for the precise differentiation of lodging grades remain to be refined. This study presents an improved AlexNet model integrated with a Local Feature Aggregation (LFA) attention mechanism and a dynamic optimization strategy for the accurate grading of soybean lodging. RGB imagery of soybean canopies during the grain-filling to early maturity stages was acquired via a multispectral unmanned aerial vehicle (UAV). A dynamic Dropout strategy was adopted to enhance model stability and mitigate overfitting, and the Particle Swarm Optimization (PSO) algorithm was employed to intelligently optimize key hyperparameters of the model. The results demonstrate that the optimized model achieved an overall accuracy of 94.23% on the test set, with an average loss of 0.0682 and an inference speed of 0.422 s/step. In independent field validation, the grading accuracies for the five lodging grades were 90.12%, 86.35%, 89.47%, 88.93%, and 92.76%, respectively, with a mean accuracy of 89.53%. The proposed model enables the rapid and precise grading of soybean lodging under field conditions, thereby providing effective technical support for intelligent field management and disaster loss assessment in soybean production.

Keywords: soybean; lodging classification; remote sensing; AlexNet model; attention module

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1. Introduction

As a globally vital source of oil and protein, soybeans suffer severe yield and quality losses due to natural environmental factors and inadequate field management practices. Lodging is a primary driver of reduced soybean yield and impaired quality [1]. Specifically, lodging refers to the agronomic phenomenon where soybean plants experience stem bending, inclination or even complete prostration on the ground due to insufficient mechanical strength of stems and roots under external stresses such as strong winds and heavy rainfall. It occurs predominantly during the pod-filling stage, when soybean plants are in a vigorous growth phase with maximum plant height and branching density. During this growth stage, crops are prone to both stem lodging and root lodging when exposed to concentrated rainfall or strong winds. Stem lodging is mainly induced by excessively long lower and

middle internodes, whereas root lodging occurs due to reduced soil adhesion caused by rainwater erosion [2]. While mild lodging can recover naturally via stem elasticity in subsequent growth stages, severe lodging disrupts the canopy structure of soybean populations. This results in leaf overlapping and a sharp decline in photosynthetic efficiency, ultimately reducing the number of effective pods and increasing the rate of shriveled grains. Studies have shown that each one-grade increase in soybean lodging severity can cause yield losses of up to 195 kg/hm^2 [3]. Lodging is not limited to soybeans; wheat is also frequently plagued by this issue. Frequent lodging in wheat can result in over 50% yield loss, reduced grain quality, and increased difficulty and cost of field harvesting due to plant toppling [4,5].

The adverse impacts of lodging on crop production are widespread. In agricultural insurance claims, lodging severity serves as the core basis for loss assessment [6]. In intelligent agricultural management, precise lodging grading is critical for guiding field remedial practices and optimizing harvest strategies. Therefore, research on the precise identification and grading of soybean lodging holds great practical significance for safeguarding the high and stable yield of soybeans.

Currently, Unmanned Aerial Vehicle (UAV) remote sensing technology, with the advantages of non-destructiveness, high efficiency and large-scale coverage, has become the mainstream method for acquiring crop lodging information [7–9]. Relevant studies on lodging monitoring via the integration of UAV data and algorithms have been extensively conducted, yet most focus on staple crops such as rice and corn, leaving notable limitations in the fine-grained classification of soybean lodging [10,11]. Machine learning-based UAV remote sensing studies have realized the identification of lodged rice with high accuracy, but only for binary classification without lodging grade differentiation [10]; though grade subdivision for corn lodging has been achieved by fusing spectral and texture features and combining morphological indices, the heavy reliance on handcrafted feature engineering leads to insufficient feature robustness under the complex weed and soil backgrounds of soybean fields [11]. Satellite remote sensing has also been applied in crop lodging research, with feature fusion and vegetation index methods improving the extraction and recognition accuracy of corn and rice lodging information [12,13], yet the limited spatial resolution of satellite images fails to capture fine lodging details of individual soybean plants or small populations, making it unsuitable for soybean lodging grade classification.

End-to-end learning-enabled deep learning has provided a novel approach for crop lodging monitoring [14], and related studies have made progress in lodging area segmentation and feature extraction via convolutional neural networks and attention mechanisms [15,16]. Nevertheless, existing deep learning models only realize the automatic segmentation of corn lodging areas without grade refinement [15], and even the introduction of attention mechanisms to enhance feature extraction only targets binary classification of wheat lodging, with no applicability for multi-grade classification [16]. In addition, single-feature-based lodging area recognition for corn suffers from poor model robustness [17], and machine learning-based rice lodging models combined with intelligent optimization algorithms are susceptible to interference from complex field backgrounds [18]. In summary, neither machine learning nor deep learning methods can meet the requirements of soybean lodging grade classification, stemming from exclusive binary classification, insufficient feature robustness, severe background interference and inadequate ability to distinguish lodging grades.

The core limitations of existing research are twofold. First, most models only achieve binary classification and lack the capacity to discriminate subtle differences between adjacent lodging grades. Second, traditional convolutional neural network models are susceptible to background interference, whereas existing attention mechanism models are

mostly general-purpose and lack optimizations tailored to the agronomic characteristics of crops. This consequently leads to insufficient specificity in the extraction of key lodging-related features.

To address these issues, a five-grade soybean lodging dataset was constructed using RGB UAV images acquired during the soybean grain-filling to early maturity stage. Key lodging-related features were enhanced through the collaborative adjustment of luminance and contrast, as well as the adaptive sharpening of lodging-affected areas. The AlexNet model was improved by embedding a soybean-specific lodging feature attention module, which directionally captures core agronomic characteristics such as stem inclination angle and canopy depression depth. A dynamic Dropout mechanism was further introduced to enhance the model's generalization performance. The framework is tailored to the agronomic characteristics of soybean lodging and targets the core pain points of fine-grained lodging classification. This study ultimately achieves rapid and accurate grading of soybean lodging, providing a technical solution for the precise and efficient assessment of soybean lodging grades.

2. Materials and Methods

2.1. Research Area and Datasets

2.1.1. Overview of the Research Area

Figure 1 illustrates the geographical location of the research area.

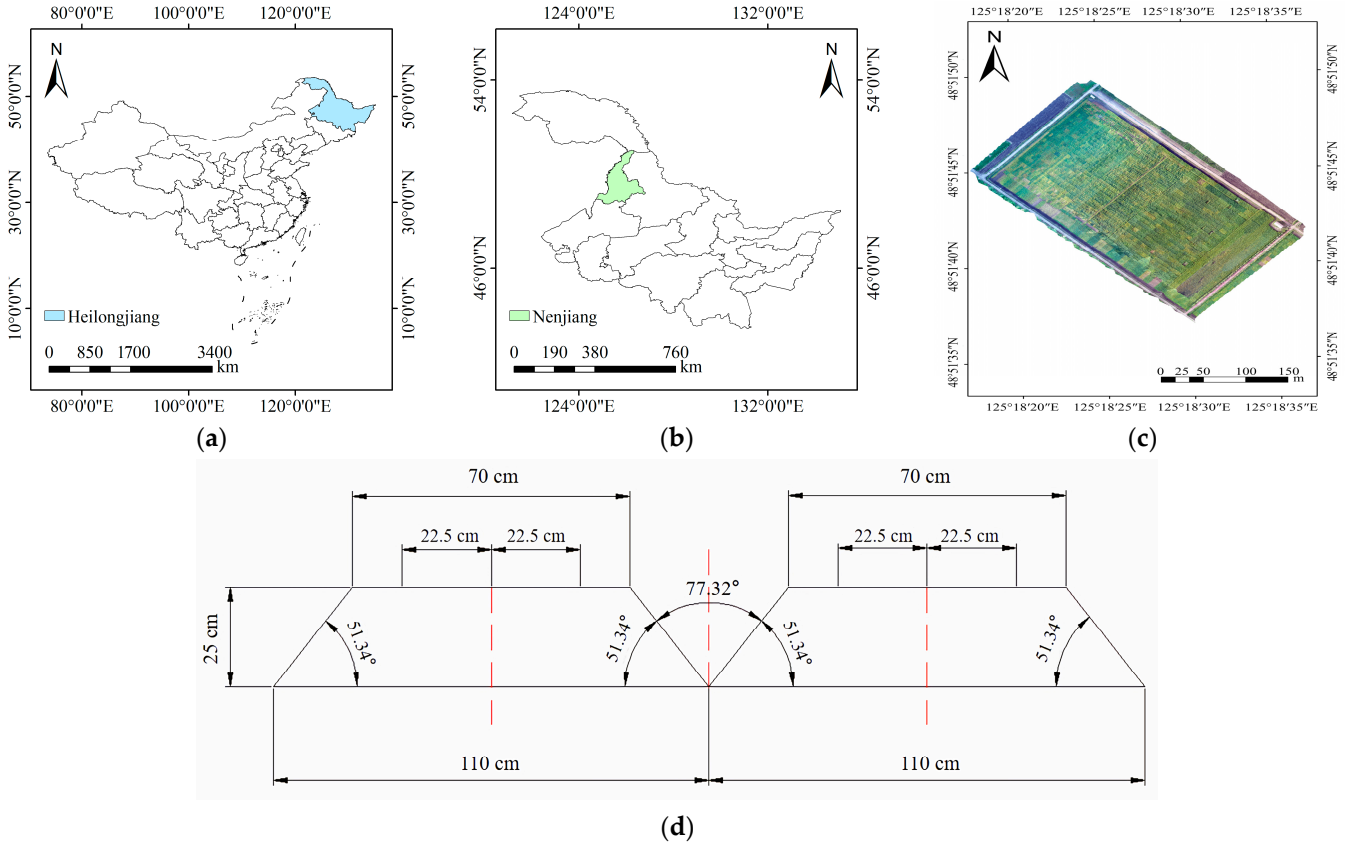

Figure 1. Geographical location of the research area. (**a**) Heilongjiang Province in China; (**b**) Nenjiang County in Heilongjiang Province; (**c**) Research area; (**d**) Planting pattern.

The research area is situated at Jianshan Farm of the Jiusan Administration Bureau, Nenjiang County, Heihe City, Heilongjiang Province, China, the planting pattern adopts three rows per 1.1 m ridge. This region features a temperate continental monsoon climate,

with ample sunshine during the soybean growing season and a substantial diurnal temperature range [19]. This region represents a typical major soybean-producing area with a high incidence of lodging. Furthermore, the research area includes hilly terrain, which can simulate complex field environments and provide ideal conditions for validating the anti-interference ability of the model.

2.1.2. Methodology

During the image acquisition stage, a Phantom 4 multispectral UAV (DJI Innovations, Shenzhen, China) was used as the primary platform. This UAV was equipped with an RGB imaging sensor, and DJI GS Pro 2.0.17 software was utilized to configure the flight parameters. Real-time adjustment of the flight attitude via this software ensured the spatial accuracy and data quality of the field image collection. In the image preprocessing stage, Adobe Photoshop 2021 was mainly used to crop the acquired original images and standardize the sizes of images from different batches, thus providing standardized data for subsequent model input.

Model construction and optimization were performed using hardware acceleration provided by the CUDA 11.7 architecture and the cuDNN library, based on the TensorFlow 2.5 deep learning framework with its built-in Keras module. The Python 3.8.18 scikit-opt library was incorporated for hyperparameter optimization.

2.2. Image Acquisition and Preprocessing

2.2.1. UAV Image Acquisition

Image acquisition was performed during the grain-filling to early maturity stage of soybean, which corresponded to September 2025 in the research area. This stage was selected because mild soybean lodging had typically recovered by this time, while lodging characteristics across different grades remained clearly distinguishable, effectively reducing interference in subsequent grading. Additionally, the soybean canopy structure stabilizes during this period, with plant height and stem rigidity reaching representative levels, ensuring that acquired images can accurately capture lodging features specific to each grade. Image acquisition was conducted under sunny and breezy weather conditions. Flight parameters were configured using DJI GS Pro software with the following key settings: a flight altitude of 25 m, a forward overlap and side overlap of 70% each, and an S-shaped flight pattern to ensure sufficient image overlap for subsequent stitching and feature verification. A vertical camera angle of 90° and a flight speed of 2.8 m/s were adopted, with image capture at regular intervals along the flight path to maintain consistency in viewing angle and exposure. The acquired original images were stored in PNG format, with a resolution of 4608 × 3456 pixels.

2.2.2. Image Preprocessing

Soybean lodging grades were classified based on core agronomic indicators, including plant inclination angle, canopy integrity, and stem bending degree. To ensure the objectivity and accuracy of grade labeling, dual verification was adopted: classification based on agronomic indicators was combined with field manual measurements, in which a protractor was used to quantify plant inclination angles and a measuring tape was employed to record variations in canopy height.

The classification standard employed in this study was established according to local agronomic requirements, actual field production conditions in the study area and expert experience, which is a targeted criterion suitable for the soybean lodging characteristics of this region.

According to the lodging angle (A), the classification was defined as A = 0°, A ≤ 15°, 15° < A ≤ 45°, A > 45°and A = 90°. The detailed soybean lodging grade division is presented in Table 1.

Table 1. The detailed soybean lodging grade division.

Lodging Grade	Division Method
Level 0	A = 0°
Level 1	A ≤ 15°
Level 2	15° < A ≤ 45°
Level 3	A > 45°
Level 4	A = 90°

Invalid images, including those with blurred edges or containing non-soybean regions such as bare soil and weeds, were first screened out via visual interpretation. Subsequently, valid images were batch-cropped to a uniform size of 255 × 255 × 3 (width × height × channels) using Adobe Photoshop, thereby standardizing the input data format for model training. During cropping, priority was given to retaining regions with complete soybean canopies, which helped reduce the interference of redundant background information on model learning. UAV remote sensing orthorectified images of different lodging grades are presented in Figure 2.

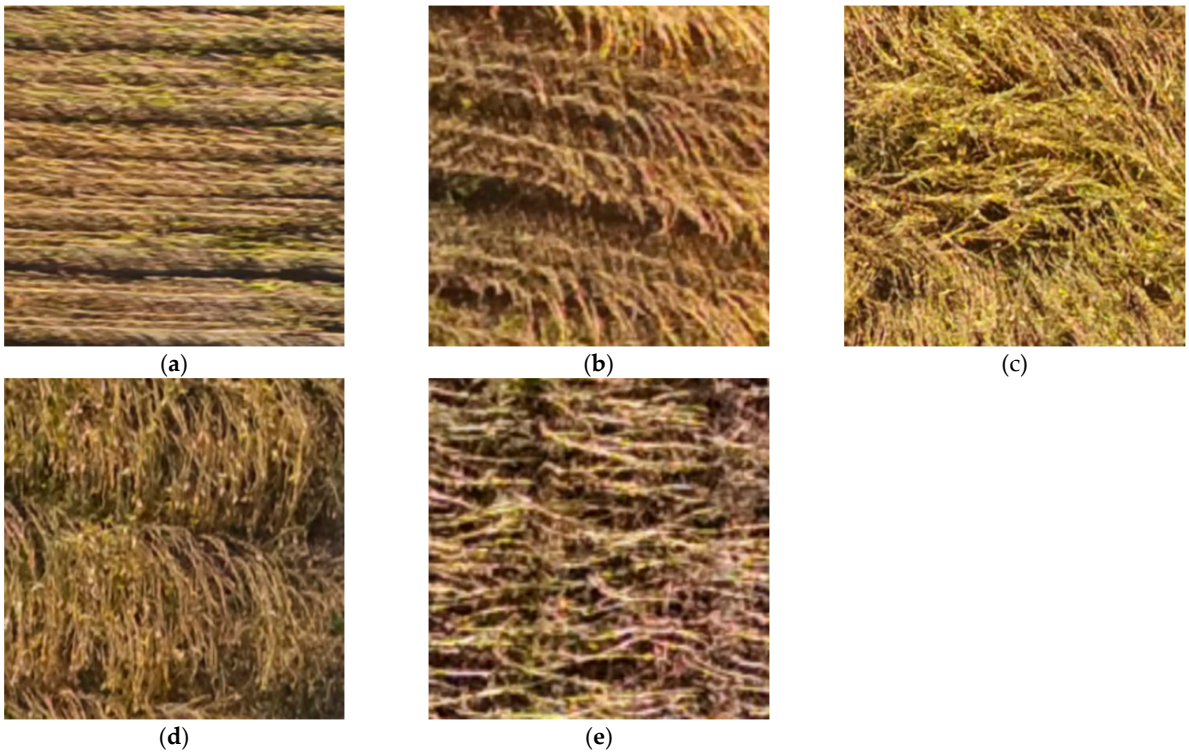

Figure 2. UAV remote sensing orthorectified images of lodging types at various levels. (**a**) Level 0; (**b**) Level 1; (**c**) Level 2; (**d**) Level 3; (**e**) Level 4.

Each subfigure represents the predominant lodging grade in the corresponding plot, and mixed minor lodging degrees may exist in the field, which conforms to the actual distribution characteristics of natural soybean lodging. An image enhancement strategy combining collaborative brightness-contrast adjustment and random flipping was adopted. Leveraging the grayscale differences between soybean leaves and soil, brightness and contrast were dynamically adjusted to enhance plant contours. All data augmentation

operations were exclusively applied to the training set; the independent validation set and test set used original non-augmented UAV images to avoid data leakage. After enhancement, the per-grade sample size of the original images increased from 500 to 1000. The enhanced dataset was split into a training set and a test set at a 3:1 ratio via stratified random splitting to ensure balanced lodging grade distribution, each grade corresponded to 750 training images and 250 test images.

Additionally, an independent validation set was further constructed from the original non-augmented enhanced dataset to monitor the training process and adjust hyperparameters. This set comprised 50 additional images per grade (250 images total) and was used to evaluate model performance during training and avoid overfitting. The independent test set was completely unseen during training and validation and only used to evaluate the final generalization performance of the trained model. The training set, validation set, and test set were strictly separated with no overlapping samples, eliminating the risk of data leakage and ensuring the objectivity of accuracy results. Image labels were set to 0–4 to align with the five lodging grades.

2.3. Construction of the Improved AlexNet Model

Based on the AlexNet model, and targeting the core requirements of soybean lodging grade classification, a lodging feature attention module, a dynamic Dropout mechanism, as well as optimizations for the fully connected layers and output layer were designed, forming a progressive structure of "feature enhancement-dynamic regularization-accurate classification". Figure 3 presents a schematic diagram of the improved AlexNet model structure.

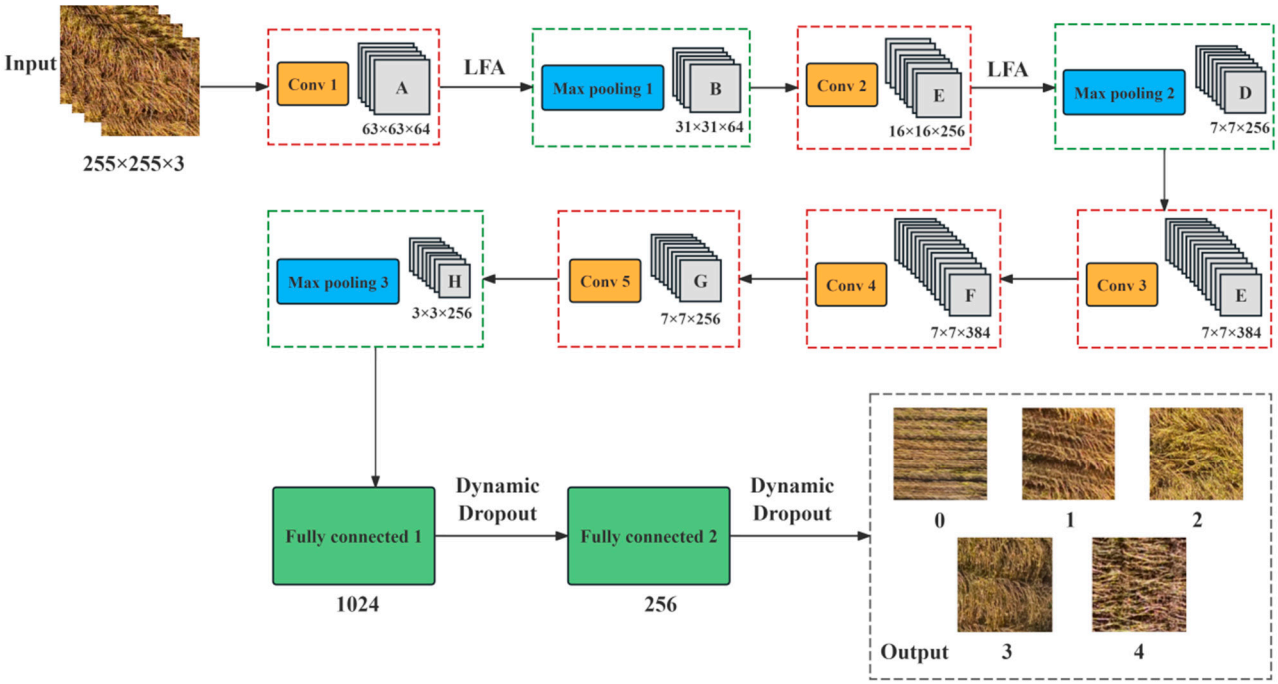

Figure 3. Schematic diagram of the improved AlexNet model structure.

The input to the AlexNet model consists of soybean lodging grading images with a size of 255 × 255 × 3. After input, the images undergo feature extraction via convolutional layers and subsequent pooling operations, generating a feature map with dimensions of 3 × 3 × 256. The convolutional kernel size is gradually reduced from 7 to 5 and then to 3, while the feature map is downsampled by half using overlapping max-pooling operations in the 1st, 2nd, and 5th layers. Following repeated feature extraction and refinement in

the 5th convolutional layer, image features are sufficiently enhanced and then fed into the fully connected layers for feature calculation and processing. Finally, the Softmax layer integrates and outputs the final classification results.

2.3.1. Convolutional Layer

The convolutional layer is the core component of a convolutional neural network (CNN). In convolution operations, it can effectively extract deep-level feature information from small pixel regions in an image, making it well-suited for image content processing [20]. The calculation process of the convolution operation is given by Equation (1).

$$Conv_{out} = \frac{Conv_{in} + 2p - F_{Conv}}{S_{Conv}} + 1 \quad (1)$$

where $Conv_{out}$ denotes the output image size (in pixels); $Conv_{in}$ denotes the input image size (in pixels); F_{Conv} denotes the convolution kernel size (in pixels); p denotes the padding size for input image data; and S_{Conv} denotes the convolution stride.

2.3.2. Design of the Lodging Feature Attention Module

The core mechanism of Local Feature Aggregation (LFA) consists of extracting local features from images, constructing image feature representations through clustering or encoding, and performing similarity comparisons based on these representations for image retrieval [21]. Notably, the LFA module in this study is not directly adopted from the original local feature aggregation framework; instead, we have made targeted structural and functional improvements tailored to the agronomic characteristics of soybean lodging for the classification task. For soybean lodging classification tasks, this study develops an LFA-based lodging feature attention module as a dedicated feature enhancement component. Its core objective is to address the limitations of the conventional AlexNet model in extracting key discriminative features for classification, such as plant inclination angle and canopy flatness. Through the synergy of lodging feature perception, spatial weight assignment, and channel feature enhancement, the module achieves targeted capture of key classification features and suppression of irrelevant noise.

Lodging feature perception first screens original soybean lodging-related features from the feature maps output by the convolutional layers, laying a foundation for subsequent weight assignment. Differences in lodging grades are primarily reflected in plant morphological deformations (e.g., inclination angle, stem bending) and canopy structural changes (e.g., flatness, coverage density). Spatial weight assignment focuses on enhancing features in plant regions while suppressing background noise (e.g., soil, weeds). Channel feature enhancement prioritizes strengthening channels that are strongly correlated with lodging grades, such as the inclination angle channel in the morphological feature branch and the flatness channel in the canopy feature branch.

The LFA module facilitates the selection of lodging-related features from raw features, enhances plant spatial regions, and further emphasizes discriminative channels. The innovation of this module is twofold:

(1) A dual-branch feature perception structure tailored to the agronomic characteristics of soybean lodging, in contrast to the single-branch feature input used in generic attention modules.
(2) Spatial and channel weight assignment based on lodging-related feature computation, which reduces feature redundancy caused by indiscriminate weighting and yields better adaptation to soybean lodging classification tasks.

2.3.3. Pooling Layer

Pooling operations reduce the volume of data processing while preserving useful feature information and mitigating the impact of noise and clutter [22]. Typically applied subsequent to convolution operations, pooling further lowers computational complexity. Max-pooling is adopted in this study, which operates by computing the maximum value of elements within a pooling window. This operation retains the most salient features in the image while minimizing information loss. The calculation process is given by Equation (2).

$$Mp_{out} = \frac{Mp_{in} - F_{Mp}}{S_{Mp}} + 1 \quad (2)$$

where Mp_{out} denotes the output size of max pooling (in pixels); Mp_{in} denotes the input size of max pooling (in pixels); F_{Mp} denotes the kernel size of the pooling layer (in pixels); and S_{Mp} denotes the pooling stride.

2.3.4. Optimization of the Fully Connected Layer and Output Layer

The fully connected layer, usually the penultimate layer in a convolutional neural network (CNN), accounts for most of the model's computational load. It stores the high-level feature information of the model and conducts image classification, thereby generating output layer results to accomplish final classification and prediction [23]. The traditional CNN architecture based on AlexNet contains two fully connected layers with 4096 neurons each. To reduce the number of trainable parameters, decrease model complexity, and speed up convergence, adjustments to the number of neurons in these layers are practical. For instance, Ni et al. modified the number of neurons in AlexNet's fully connected layer to 1024 for peanut pod recognition, achieving an accuracy of 87.73% and enabling accurate and rapid classification of different peanut pod types [24]. Ren adjusted the first fully connected layer of AlexNet to 512 neurons and removed the second, constructing a flower recognition model with an accuracy of 73.82% [25].

In this study, with reference to the optimization method proposed by Li et al. [26], the number of neurons in the first fully connected layer was set to 1024, and that in the second fully connected layer was set to 256, thereby reducing model parameter redundancy. Additionally, considering the five soybean lodging grades, the number of neurons in the third fully connected layer was adjusted to 5, which directly outputs the classification probability for each grade. The output layer employs the Softmax function to convert the output of the third fully connected layer into a probability distribution, and its calculation process is given by Equation (3) [27]:

$$S_r = \frac{\exp(a_{rx})}{\sum_{k=1}^{3} \exp(a_{rk})} \quad (3)$$

where S_r denotes the probability that the r-th soybean image belongs to the x-th class; a_{rx} denotes the product of the r-th element in the vector and the x-th class; a_{rk} denotes the product of the r-th element in the vector and the k-th class; and k denotes the total number of lodging grade classes.

2.3.5. Design of the Dynamic Dropout Mechanism

The Dropout mechanism mainly involves randomly deactivating specific neuron nodes according to a predefined rate during convolutional neural network training. This deactivation ensures that certain node units are excluded from model calculations in each training iteration, thereby reducing the computational burden during training. Owing to the varying internal network structure in each training round, inputting the same data

leads to different training processes, thus preserving feature diversity [28]. Different from the traditional fixed-rate Dropout algorithm that is directly applied in most models, the dynamic Dropout mechanism proposed in this study is an improved version optimized for the soybean lodging grade classification task.

The conventional Dropout structure in AlexNet lacks the ability to adjust dynamically based on classification errors during training. In this study, dynamic Dropout modules were introduced after the first and second fully connected layers, respectively. During model training, the classification error rate of adjacent lodging grades was calculated in real time, and the dropout rate was adjusted dynamically accordingly. Meanwhile, the dropout rate was updated after each iteration. This design enables the model to strengthen its generalization ability when errors are high in the early training stage and retain key features when errors are low in the later training stage.

2.3.6. Intelligent Hyperparameter Optimization Based on PSO

The hyperparameter configuration of the traditional AlexNet model relies heavily on manual trial-and-error, which is not only inefficient but also prone to trapping model training in local optima, limiting the model's full performance for soybean lodging classification, the core objective of this study. The standard PSO algorithm was adaptively modified by optimizing its parameter search range and update strategy, which were tailored to the hyperparameter characteristics of the improved AlexNet model and the practical demands of soybean lodging classification. The PSO algorithm leverages information sharing among individuals in a population to drive the entire population's movement through an evolutionary process-from disorder to order in the problem-solving space-thereby obtaining the optimal solution [29]. The specific steps are illustrated in Figure 4.

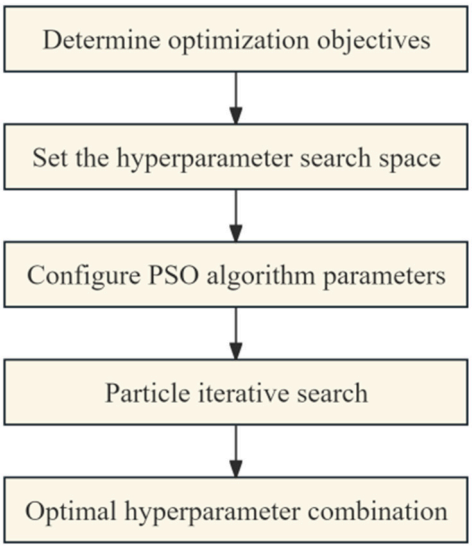

Figure 4. Intelligent optimization steps of the PSO algorithm.

The optimization scheme focuses on addressing the limitations of traditional hyperparameter configuration to enhance the model's adaptability to UAV soybean lodging images. PSO algorithm parameter configuration employed a dynamic inertia weight strategy, which balances global search and local optimization capabilities, and cooperates with a fixed acceleration factor to efficiently converge to the optimal hyperparameter combination for soybean lodging classification.

Additionally, the model's activation function remains the ReLU function, which is conducive to feature extraction of soybean lodging images and alleviates gradient diffusion

during training. The number of training epochs is set to 300 to ensure adequate model training and reliable classification results.

2.4. Model Performance Evaluation and Verification Methods

The average accuracy, average loss value, iteration time, and adjacent-level misclassification rate were adopted as evaluation metrics for model performance. The adjacent-level misclassification rate is defined as the proportion of mutually misclassified samples between Level 0 and Level 1, as well as between Level 2 and Level 3, relative to the total number of samples. This metric reflects the model's ability to distinguish subtle differences between adjacent lodging grades.

A three-tiered validation strategy was employed to conduct systematic verification. The first tier focused on training and test set validation: performance differences were compared among the original AlexNet model, an improved AlexNet model without the LFA module (equipped only with the dynamic Dropout mechanism), and the proposed model. This tier validated the effectiveness of the innovative modules from the perspective of basic experimental data.

The second tier involved independent validation set validation: the 250-image independent validation set was fed into the three aforementioned models. Emphasis was placed on evaluating the models' generalization performance on unseen data, with particular attention to the reduction in adjacent-grade misclassification rates. This step aimed to clarify the performance stability boundary of the models.

The third tier consisted of field validation: the five-point sampling method was used to select five representative plots in the experimental area, covering diverse terrains such as highlands and flatlands. Forty images were captured by UAV for each plot, yielding a total of 200 field images. These images were input into the proposed model to obtain lodging grading results, which were then compared with manual field measurements (accurate grades obtained using protractors and measuring tapes). By calculating the classification accuracy and misclassification rate for each lodging grade, the applicability of the model in complex real-world field environments was systematically verified.

3. Results

3.1. Comparison of Model Performance Before and After Image Enhancement

To verify the independent effectiveness of the proposed image enhancement strategy and determine whether it can lay a better foundation for feature extraction in the soybean lodging classification model, the original AlexNet model was used as the benchmark. With all other experimental conditions strictly controlled to be consistent, training and testing were conducted separately on the original (pre-enhancement) dataset and the enhanced dataset. Figure 5 presents the trends of test accuracy and loss of the AlexNet model on the datasets before and after enhancement.

As shown in Figure 5a, the model trained on the non-enhanced dataset achieved a test accuracy of 0.8 after approximately 25 iterations. The accuracy growth slowed and stabilized at approximately 0.85 after 100 iterations. In contrast, the model trained on the enhanced dataset reached an accuracy of 0.85 after only 15 iterations, tended to stabilize after around 50 iterations, and remained stable within the range of 0.9–0.95 after 300 iterations. This significant difference reflects the dual improvement of the image enhancement strategy on both model convergence speed and prediction accuracy.

From the loss trend shown in Figure 5b, it can be observed that both models entered a stable phase after 150 iterations, but with notable differences in stability. For the model without image enhancement, the loss remained above 1.4 in the initial iteration stage, with a slow decline rate. Even in the later iteration stage (150–300 iterations), although the loss

was generally below 0.2, obvious fluctuations still occurred at individual iteration steps. This indicates that the model was highly sensitive to noise and redundant features in the original data, resulting in unstable fitting during the later training stage. For the model with image enhancement, the loss decreased significantly faster, stabilized completely after 150 iterations, and remained consistently within the range of 0–0.2 without obvious fluctuations, showing a highly smooth curve.

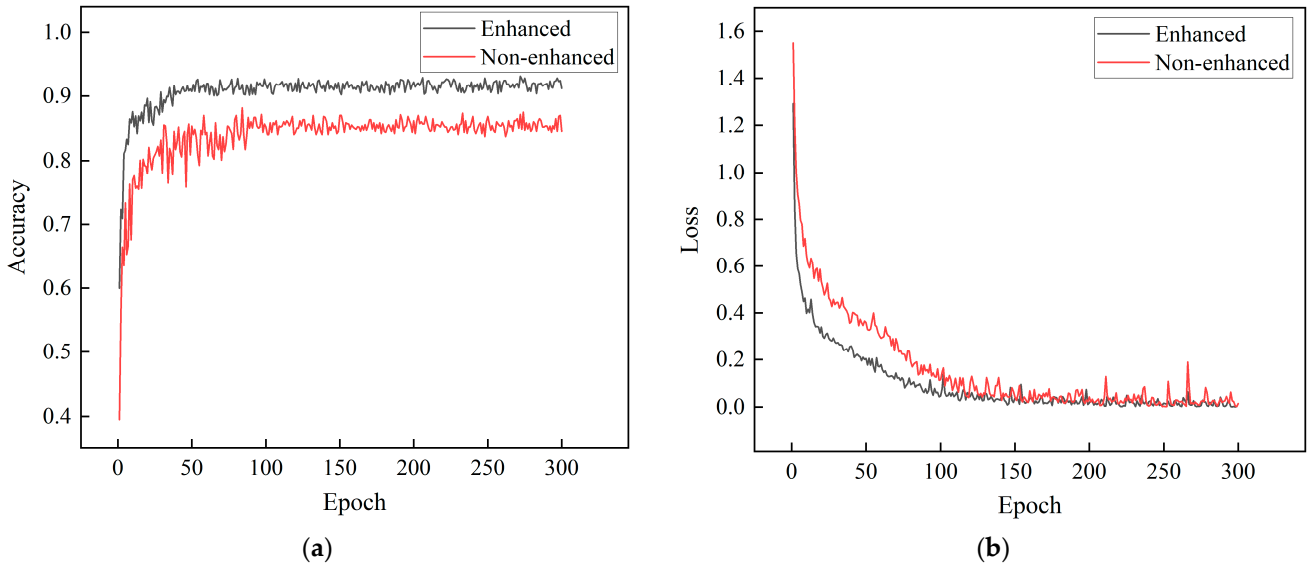

Figure 5. Trends of test accuracy and loss of the AlexNet model on the dataset before and after enhancement. (**a**) Trend of test accuracy; (**b**) Trend of loss.

The core reason for this difference is that image enhancement augments sample diversity, allowing the model to learn hierarchical core features more comprehensively during training. In contrast, owing to insufficient feature discrimination and limited sample diversity in the original dataset, the model may still exhibit fitting fluctuations in later iterations due to the interference of individual samples.

3.2. Preliminary Model Selection and Benchmark Comparison

To scientifically screen the optimal baseline model for soybean lodging grade classification, a systematic benchmark comparison experiment was conducted under completely consistent experimental conditions. The selection strictly adhered to the core requirements of UAV-based agricultural remote sensing applications, focusing on three dimensions: classification accuracy for fine-grained lodging grades, fitting stability reflected by loss values, and computational efficiency represented by inference time. Four representative convolutional neural network models with different structural characteristics were included in the comparison: AlexNet, the classic lightweight convolutional neural network; VGG16, a deep network with stacked convolutional layers; ResNet18, a residual network designed to solve the gradient vanishing problem; and MobileNetV2, a lightweight model based on depthwise separable convolution. All models were trained using the same dataset, hyperparameter settings, training epochs, and hardware platform to ensure the objectivity and comparability of the experimental results. The detailed results of the benchmark comparison are presented in Table 2.

Table 2. The detailed results of the benchmark comparison.

Model	Average Accuracy of Testing Set (%)	Average Loss	Iteration Time (s/step)
AlexNet	83.89	0.1601	0.454
VGG16	79.94	0.2077	1.472
ResNet18	81.17	0.1883	0.973
MobileNetV2	75.63	0.2322	0.326

In terms of overall test accuracy, AlexNet achieved a performance of 83.89%, which is 2.72 percentage points higher than ResNet18 (81.17%), 3.95 percentage points higher than VGG16 (79.94%), and 8.26 percentage points higher than MobileNetV2 (75.63%). This significant accuracy advantage fully proves that AlexNet has a stronger ability to capture the subtle morphological differences between adjacent soybean lodging grades (such as stem inclination angle and canopy flatness) compared with other models, which is the core premise for realizing accurate lodging grade classification.

In terms of fitting stability, AlexNet obtained the lowest average loss of 0.1601 among all models. This value is 0.0282 lower than ResNet18 (0.1883), 0.0476 lower than VGG16 (0.2077), and 0.0721 lower than MobileNetV2 (0.2322). The minimum average loss indicates that AlexNet can effectively learn the discriminative features of soybean lodging under the same training conditions, avoid overfitting or underfitting, and have strong generalization potential, which lays a solid and reliable foundation for subsequent targeted improvement and optimization.

In terms of computational efficiency, AlexNet still maintained the leading advantage, with an inference time of 0.454 s per sample. This inference speed is 0.519 s faster than ResNet18 (0.973 s/step) and 1.018 s faster than VGG16 (1.472 s/step), which means that AlexNet has obvious advantages in processing large-volume UAV remote sensing images in large-scale soybean fields. Although MobileNetV2 has a shorter inference time (0.326 s/step) due to its ultra-lightweight structure, its classification accuracy and fitting stability are far lower than AlexNet, and it cannot meet the precision requirement of soybean lodging grade classification.

Comprehensive analysis of the three core evaluation metrics shows that AlexNet has the best overall performance among the four candidate models. VGG16 and ResNet18, due to their complex network structures, not only have lower classification accuracy and fitting stability than AlexNet but also suffer from low computational efficiency, which is not conducive to on-site real-time deployment in agricultural production. MobileNetV2, while pursuing computational efficiency, excessively sacrifices feature extraction capability, resulting in poor classification performance and failing to complete the fine-grained lodging grade classification task. Therefore, based on the objective experimental results, AlexNet was determined as the baseline model in this study, and a series of targeted improvement strategies including the LFA attention module and dynamic Dropout mechanism were subsequently applied to it to further enhance its classification performance on the premise of retaining its inherent advantages.

3.3. Comparison of Training and Testing Performance of the Improved Models

To precisely quantify the independent contribution of each module in the model optimization process, eliminate interference from data augmentation, and ensure the objectivity of experimental conclusions, a performance comparison was conducted among the original AlexNet, an improved model without the LFA module (denoted as "AlexNet-Dynamic Dropout"), and the proposed innovative model (denoted as "AlexNet-LFA-Dynamic Dropout") based on the original pre-augmentation dataset. This systematic

comparison serves as an ablation experiment to isolate the specific effect of the LFA module on capturing agronomically meaningful lodging features for grade differentiation. The comparison results of the training and testing performance of the improved models are presented in Table 3.

Table 3. The comparison results of the training and testing performance of the improved models.

Model Type	Average Accuracy of Training Set (%)	Average Accuracy of Testing Set (%)	Average Loss	Iteration Time (s/Step)	Misclassification Rate of Adjacent Levels (%)
Original AlexNet	89.76	83.89	0.1601	0.454	18.72
AlexNet-Dynamic Dropout	92.15	87.62	0.1023	0.441	12.55
AlexNet-LFA-Dynamic Dropout	96.58	94.23	0.0682	0.422	7.31

As can be seen from Table 3, after introducing the dynamic Dropout mechanism, the test set average accuracy of AlexNet-Dynamic Dropout increased by 3.73% compared with the original AlexNet, the average loss decreased by 0.0578, and the adjacent-level misclassification rate was reduced by 6.17%. These results demonstrate that dynamic Dropout effectively improves the model's generalization ability and level discrimination ability by adaptively adjusting the regularization strength.

The test set average accuracy of the proposed AlexNet-LFA-Dynamic Dropout further increased by 6.61% compared with AlexNet-Dynamic Dropout, the average loss decreased by 0.0341, the adjacent-level misclassification rate was reduced by 5.24%, and the iteration time was shortened by 0.019 s/step. This indicates that the LFA module significantly enhances the model's classification accuracy and efficiency by strengthening key feature extraction, without introducing an obvious additional computational burden.

Under the premise of eliminating interference from image enhancement, model structure optimization effectively improves soybean lodging classification performance, and the two modules present a clear synergistic effect. Dynamic Dropout ensures the generalization ability of the model, while the LFA module strengthens the efficiency of key feature extraction. Together, they alleviate the core problems of the original AlexNet in lodging classification, namely, "strong background interference and weak discrimination between adjacent grades".

3.4. Verification Results of Independent Validation Set

The independent validation set (consisting of 250 images) was fed into the three models, and the performance comparison results of different models on the independent validation set are presented in Table 4. The results show that AlexNet-LFA-Dynamic Dropout achieved an average accuracy of 89.20% on the independent validation set, representing an improvement of 6.80% over the original AlexNet. Furthermore, the misclassification rates for grades 0–1 and 2–3 decreased by 12.41% and 11.72%, respectively. This demonstrates that the generalization ability of the proposed model is significantly superior to that of traditional models, maintaining high grading accuracy even for unseen samples. This is attributed to the stable feature extraction capability of the LFA module for key traits. Even when facing interference from varying illumination and terrain conditions in new samples, the model can still focus on core features such as plant inclination angle and canopy flatness, thus reducing misclassification caused by environmental factors.

Table 4. The performance comparison results of different models on the independent validation set.

Model Type	Average Precision (%)	Misclassification Rate at Level 0–1 (%)	Misclassification Rate at Levels 2–3 (%)
Original AlexNet	82.40	22.13	19.87
AlexNet-Dynamic Dropout	86.80	15.36	13.24
AlexNet-LFA-Dynamic Dropout	89.20	9.72	8.15

3.5. Field Verification Results

The classification results of the AlexNet-LFA-Dynamic Dropout model on 200 field verification images are presented in Table 5.

Table 5. Classification accuracy of each level of the AlexNet-LFA-Dynamic Dropout model in field validation.

Lodging Grade	Classification Accuracy (%)	Misclassification Rate (%)	Main Misclassification Levels
Level 0	90.12	9.88	Level 1 (7.62%)
Level 1	86.35	13.65	Level 0 (9.72%)
Level 2	89.47	10.53	Level 3 (8.15%)
Level 3	88.93	11.07	Level 2 (8.56%)
Level 4	92.76	7.24	Level 3 (5.18%)
Average	89.53	10.47	

The data in Table 5 reveals a clear correlation between classification performance and different lodging grades. Specifically, Level 4 (severe lodging) achieves the highest classification accuracy of 92.76%, with a corresponding misclassification rate of only 7.24%. Notably, the proportion of misclassifications mainly assigned to Level 3 is merely 5.18%. The primary reason for this excellent performance is that severely lodged plants lie completely flat on the ground, exhibiting obvious morphological differences from plants of other grades, allowing the model to rapidly and accurately identify their unique morphological characteristics.

Level 1 (mild lodging) shows the lowest classification accuracy of 86.35%, with a misclassification rate of 13.65%. Its main misclassification direction is toward Level 0, accounting for 9.72%. Mildly lodged plants have a small inclination angle and high morphological similarity to non-lodged (Level 0) plants, which is a key factor leading to misclassification. Nevertheless, the model has effectively reduced such confusion risk through structural optimization.

The classification accuracies for Level 0 (no lodging), Level 2 (moderate lodging), and Level 3 (moderately severe lodging) are 90.12%, 89.47%, and 88.93%, respectively, indicating stable overall performance. The main misclassification direction for Level 0 is toward Level 1, while Level 2 and Level 3 show mutual misclassification, which is closely related to the morphological transition between adjacent lodging grades. However, the misclassification rates for both grades are controlled at approximately 8%, representing a relatively low level.

From the overall performance, the AlexNet-LFA-Dynamic Dropout model achieves an average classification accuracy of 89.53% for various lodging grades, with an average misclassification rate of 10.47%. The misclassification rate between adjacent grades ranges from 5.18% to 9.72%. The proposed model demonstrates strong reliability and applicability in practical field application scenarios.

3.6. Spatial Distribution Mapping of Soybean Lodging Grades

To visually demonstrate the predictive performance of the proposed AlexNet-LFA-Dynamic Dropout model in real-world scenarios and reveal the spatial distribution of

different soybean lodging grades within the experimental area, this study selected a complete experimental field as the research object. Based on the batch prediction results of soybean lodging grades obtained by the model, the spatial distribution map of soybean lodging grades shown in Figure 6 was constructed.

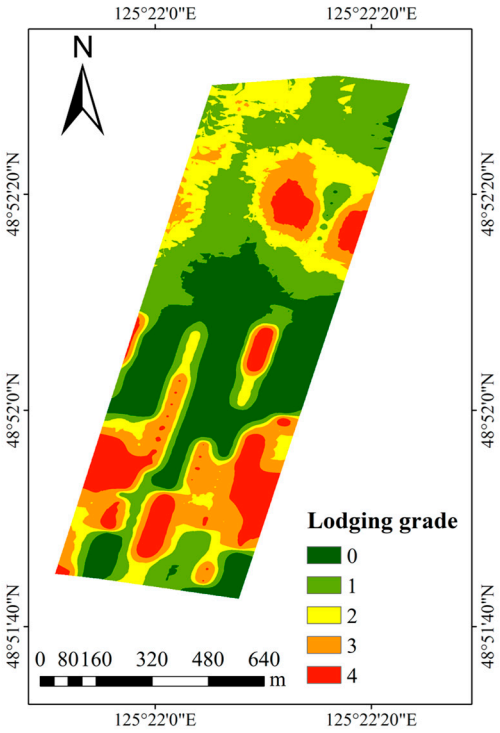

Figure 6. Spatial distribution map of soybean lodging grades.

As shown in Figure 6, the spatial distribution map of soybean lodging grades in the test area uses different color shades to represent Level 0 (no lodging), Level 1 (mild lodging), Level 2 (moderate lodging), Level 3 (moderately severe lodging), and Level 4 (severe lodging). Essentially, this spatial distribution map converts the abstract initial model prediction results into specific spatial distribution information. It provides a spatial foundation for subsequent research on exploring the causes of soybean lodging grade differences in the experimental field, screening lodging-resistant soybean varieties, and optimizing field lodging prevention and control strategies.

4. Discussion

4.1. Advantages of the LFA Module

The LFA module proposed in this study overcomes the limitation of conventional attention modules that perform indiscriminate feature extraction, enabling targeted enhancement of agronomically relevant traits. Its superior performance is reflected in synergistic improvements across multiple dimensions.

In terms of structural adaptability, the LFA module adopts a dual-branch perception architecture tailored to the agronomic characteristics of soybean lodging, as opposed to the single-convolution feature extraction mechanism employed by generic attention modules. This design aligns with the practical requirements of lodging grade classification, thereby enhancing the specificity of feature extraction. Comparative experiments demonstrate that, compared with single-branch attention modules, the dual-branch structure further reduces the adjacent-level lodging misclassification rate, which directly contributes to the high classification accuracy achieved in this study and improves the reliability of lodging grading in real-world field environments. Ablation experiment results provide

quantitative evidence for the LFA module's ability to capture agronomically meaningful lodging features: the model integrated with the LFA module achieves a 5.24% reduction in adjacent-level misclassification rate compared with the model only with dynamic Dropout, and an 11.41% reduction compared with the original AlexNet. This significant improvement in distinguishing adjacent lodging grades confirms that the LFA module is not a general attention block but is effective in extracting fine-grained agronomic features (e.g., stem inclination angle, canopy flatness) that are critical for soybean lodging grade classification. The reduction in adjacent-grade misclassification rate from 18% to 7% has important practical implications for agricultural insurance loss evaluation and field management decision-making, as accurate differentiation of adjacent lodging grades is the core basis for determining insurance compensation standards and formulating targeted field remedial measures.

Regarding weight allocation rationality, both spatial and channel weights in the LFA module are calculated exclusively based on lodging-related feature descriptors. This effectively mitigates the common issue in conventional modules where background regions are inappropriately assigned high weights, ensuring the efficiency and relevance of feature extraction. This focused feature learning strategy helps the model maintain stable and accurate identification even under complex field conditions, which is critical for practical UAV-based lodging monitoring.

Beyond soybean lodging assessment, the design paradigm of the LFA module holds broader applicability for crop disaster grade classification. By adjusting the perception branches and weight calculation logic to match the unique agronomic features of specific disasters, the module can be flexibly migrated to other crop-disaster systems, demonstrating its good generalizability. This agronomy-guided module design is the core conceptual difference from generic attention modules used in existing agricultural remote sensing studies, which lack customization for crop disaster characteristics and often extract non-discriminative general image features.

4.2. Dynamic Dropout and PSO Hyperparameter Optimization

In this study, Dynamic Dropout is designed to stabilize the feature extraction process of the LFA module and reduce overfitting during model training, which is critical for improving the robustness of soybean lodging classification using UAV images. By adaptively adjusting the dropout rate, this strategy effectively suppresses the interference caused by unstable feature extraction in the early training stage and gradually strengthens the retention of effective lodging-related features as the training process stabilizes, thus promoting faster model convergence and more reliable feature learning. By reducing overfitting and enhancing feature stability, Dynamic Dropout helps the model achieve consistent performance between laboratory testing and actual field verification.

To further improve the feature extraction performance of the LFA module, the PSO algorithm is adopted in this work for the adaptive optimization of its weight coefficients. This targeted optimization strategy avoids the instability and inefficiency of manual parameter tuning and ensures that the model can better capture the key visual characteristics of soybean lodging. Experimental results illustrate that this intelligent hyperparameter optimization scheme significantly improves the overall classification accuracy of the model, which confirms the effectiveness of automated optimization for agricultural image classification tasks. The combined use of Dynamic Dropout and PSO provides a feasible and effective scheme for improving deep learning models in soybean lodging grading, which can also be referenced for similar agricultural vision tasks.

The synergistic effect of the two strategies further reduces the adjacent-grade misclassification rate and ensures the stability of model performance in field verification, which

is crucial for practical applications: for farmers, the stable and accurate lodging grade classification results enable the formulation of targeted field management measures (e.g., artificial straightening for mild lodging, topdressing with nitrogen and potassium fertilizer for moderate lodging, early harvest for severe lodging) to minimize yield losses; for agricultural insurance companies, the accurate differentiation of lodging grades provides a reliable and objective basis for loss assessment and compensation standard formulation, avoiding disputes caused by inaccurate lodging grade identification.

4.3. Research Limitations and Future Perspectives

A notable limitation of the current study is that the model was trained exclusively on datasets containing two soybean varieties from Jianshan Farm, Heilongjiang Province, and its adaptability to other soybean varieties remains unvalidated. The single research site and moderate dataset size also raise concerns about generalization to other soybean-producing areas and planting conditions; variations in soil type (e.g., black soil, cinnamon soil, fluvo-aquic soil), planting density (e.g., high-density interplanting, conventional planting), and lighting conditions (e.g., overcast, direct sunlight, morning/afternoon light) may affect the model's performance by altering the morphological features of soybean lodging and the background contrast of UAV images. Specifically, different soil types may cause changes in soil background grayscale, leading to interference in feature extraction; high planting density may result in severe canopy overlapping, reducing the model's ability to identify individual plant inclination angles; and extreme lighting conditions may cause overexposure or underexposure of UAV images, blurring key lodging features such as stem bending and canopy depression. Given the significant inter-varietal differences in plant height, stem toughness, and lodging resistance mechanisms, it is hypothesized that adjusting the convolution kernel size in the feature perception branches of the LFA module will be necessary to accommodate different varieties.

To address this limitation, future work will focus on constructing a generalized dataset encompassing multiple soybean varieties and geographic regions covering different soil types, planting densities, and growing seasons, which will enable systematic verification and improvement of the model's universality. Additionally, transfer learning techniques will be introduced to fine-tune the proposed model on new datasets, and data augmentation strategies will be further optimized (e.g., adding color jitter, rotation, and perspective transformation) to enhance the model's adaptability to varying environmental and agronomic conditions.

Another limitation is that the current model relies solely on RGB image features, without the integration of UAV multispectral data such as the Normalized Difference Vegetation Index (NDVI), which is highly complementary to morphological features. As a well-recognized indicator for quantifying plant vitality, NDVI has been widely documented in agronomic studies for its ability to reflect physiological changes in soybeans after lodging. The integration of NDVI data with morphological features extracted from RGB images will establish a dual-dimensional feature system (morphological–physiological), which is expected to strengthen the feature discriminability of the LFA module, further reduce the misclassification rate of adjacent lodging grades, and provide a new direction for model optimization in precision agriculture applications.

To further promote practical application, future research will also explore the deployment of the proposed model on lightweight or mobile platforms, to realize real-time lodging grading and field-level decision support for farmers and agricultural management departments.

5. Conclusions

This study addresses the key challenges in existing soybean lodging classification research, including weak specificity in feature extraction, high misclassification rates among adjacent grades, and insufficient model generalization ability. These issues were resolved via the joint design of UAV data acquisition and deep learning model optimization. The main conclusions are summarized as follows:

(1) The improved AlexNet model, which integrates a lodging feature attention module and dynamic hyperparameter optimization, achieves substantial performance improvements. This enhancement not only overcomes the limitations of traditional CNNs in soybean lodging classification but also satisfies the dual requirements of high precision and high efficiency for lodging classification in practical agricultural production.

(2) The Lodging Feature Attention module employs a three-stage framework consisting of lodging feature perception, spatial weight assignment, and channel feature enhancement. This framework enables targeted extraction of core grading features, including plant inclination angle and canopy flatness, while effectively suppressing background noise from soil, weeds, and other non-target factors. The dynamic Dropout mechanism inserted between fully connected layers can adaptively adjust the dropout rate based on real-time training errors. When combined with the particle swarm optimization algorithm to determine the optimal hyperparameter combination, this mechanism further strengthens the generalization ability of the model.

(3) Field validation results demonstrate that the improved model exhibits strong practical applicability. It can adapt to soybean lodging grading tasks in complex field environments, providing reliable and accurate technical support for intelligent soybean field management and agricultural insurance loss assessment. The significant reduction in adjacent-grade misclassification rate directly addresses the practical pain points of inaccurate lodging grade differentiation in agricultural production and insurance assessment, ensuring that farmers and agricultural management departments can make science-based decisions and that insurance companies can formulate fair compensation plans. Beyond soybean research, the model offers a replicable technical paradigm for disaster grade monitoring of other crops. It also holds substantial reference value for promoting the development of precision monitoring technologies for crop disasters, thereby facilitating the advancement of agricultural intelligence.

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